Extended Sustainable Supply Chain: Pathways to Sustainability through Consumer Behavior Change

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Firouzeh Taghikhah declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Information, System, Modeling, Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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ABSTRACT

In today's growing economy, overconsumption and overproduction have accelerated environmental deterioration worldwide. Consumers, through unsustainable consumption patterns, and producers, through production based on traditional resource depleting practices, have contributed significantly to the socio-environmental problems. Consumers and producers are linked by supply chains, and as the idea of sustainable development has become seen as a way to reverse socio-environmental degradation, it has also started to sprout in research on supply chains. We look at the evolution of research on sustainable supply chains and show that it is still largely focused on the processes and networks that involve the producer and the consumer, hardly taking into account consumer behavior and its influence on the performance of the producer and the supply chain itself. We conclude that we cannot be talking about sustainability, without extending the supply chains to account for consumers' behavior and their influence on the overall system performance. In Chapter 2, a conceptual framework is proposed to explain how supply chains can become sustainable and how their economic and socio-environmental performance can be improved by motivating consumer behavior toward green consumption patterns, which, in turn, motivates producers and suppliers to change their operations.

In the thesis we focus on agro-food production-consumption, which is an important element of the sustainability agenda. The current intense food production-consumption is one of the main sources of environmental pollution and contributes up to 25-30% of anthropogenic greenhouse gas emissions. Organic farming is a potential way to reduce environmental impacts by excluding synthetic pesticides and fertilizers from the process. Organic food has important environmental and health benefits, decreasing the toxicity of agricultural production, retaining carbon, and improving overall soil quality, and generally the resilience of farming. Despite the recorded 20% growth in organically managed farmland, its global land area is still far less than could be expected, only 1.4%. Increasing consumers' demand for organic food reinforces the rate of organic farming adoption and the level of farmers' risk acceptance when transitioning to organic.

Increasing demand for organic food is an important pathway towards sustainable food systems. In Chapter 3, we explore this consumer-centric approach by developing a theoretically- and empirically-grounded agent-based model. Three behavioral theories – theory of planned behavior, alphabet theory, and goal-framing theory – describe individual food purchasing decisions in response to policies. We take wine sector as an

example to calibrate and validate the model for the case study of Sydney, Australia. The discrepancy between consumer intention and purchasing behavior for organic wine can be explained by a locked-in vicious cycle. We assess the effectiveness of different policies such as wine taxation, and informational-education campaigns to influence consumer choices. The model shows that these interventions are non-additive: raising consumer awareness and increasing tax on less environmentally friendly wines simultaneously is more successful in promoting organic wine than the sum of the two policies introduced separately. The phenomenon of undercover altruism amplifies the preference for organic wine, and the tipping point occurs at around 35% diffusion rate in the population. This chapter provides policy recommendations to help decision-makers in the food sector make informed decisions about organic markets.

Chapter 4 focuses on modeling the interplay between consumer preferences and socio-environmental issues related to agriculture and food production. We operationalize the novel extended agro-food supply chain concept and simulate adaptive behavior of farmers, food processors, retailers, and customers. Not only the operational factors (e.g., price, quantity, and lead time), but also the behavioral factors (e.g., attitude, perceived control, social norms) of food suppliers and consumers are considered in order to foster organic farming. We propose an integrated modeling approach combining agent-based, discrete-event, and system dynamics modeling for the case of a wine supply chain. The model undergoes standard testing procedures including calibration, validation and uncertainty quantification before being used for scenarios analysis and optimization. Findings demonstrate the feasibility and superiority of the proposed model over the traditional sustainable supply chain models in incorporating the feedback between consumers and producers, and analyzing management scenarios that can urge farmers to expand organic agriculture. Results further indicate that demand-side participation in transition pathways towards sustainable agriculture can become a time-consuming effort if not accompanied by the middle actors between consumers and farmers. In practice, our proposed model may serve as a decision-support tool to guide evidence-based policymaking in the food and agriculture sector.

In Chapter 5, we empirically examine purchasing behavior considering planned, impulsive, and unplanned decisions of consumers for an organic wine case study. A comprehensive theoretical framework integrating the theory of planned behavior, the theory of interpersonal behavior, impulsive buying theory, alphabet theory, and goal framing theory helps us to identify possibly influential behavioral factors, including cognitive and affective ones, driving consumers' organic wine choices. Accordingly, we

surveyed 1003 Australian wine consumers living in the City of Sydney. The descriptive analysis presents a gap between intention and behavior where 80% of consumers have a positive willingness to pay for organic products, but only 20% are actual organic wine shoppers. The correlation analysis reports strong correlations between factors confirming the validity of the proposed framework. We then use supervised machine learning method - classification algorithms including random forest, decision tree, logit regression, and support vector machine - to estimate the organic wine preferences as well as unsupervised machine learning method - the DBSCAN clustering algorithm - to segregate consumers based on their similarity. Comparing the results of methods, we notice that consumers' intention and behavior are highly influenced by behavioral factors as well as shopping, and drinking-related patterns while the effects of socio-demographic factors are small. Moreover, the classification algorithm emphasizes the role of hedonic, gain and normative cues in guiding behavior, whereas the clustering algorithm reveals the dual effects of emotions and impulsiveness in choosing organic products. Our findings have direct applications for industry and policymakers aiming at promoting organic food and facilitating demand-side solutions in a transition to sustainable agriculture.

This analysis has direct implications for further research on the topic, which we outline in the conclusion part.

Keywords: Sustainable supply chain, complex systems, organic food, pro-environmental behavior, integrated modeling, machine learning.

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Chapter 1:

General Introduction

1.1. Motivation for the research

People across the world are experiencing significant environmental, health, and economic impacts caused by anthropogenic changes in the biophysical environment, loss of biodiversity, depletion of natural resources, and climate change. The planet is getting warmer, glaciers are melting, cloud forests are drying, plastic pollution is choking the oceans, biodiversity is rapidly declining, and extreme weather conditions are becoming more frequent (Organization 2017). The recent catastrophic bushfires in Australia which have devastated more than five million hectares of land and killed 500 million animals is a good example of the transitions that we are experiencing. In facing today's crises, both adaptation and mitigation actions are essential. Mitigation refers to the preventive actions to avoid contributing to environmental degradation, while adaptation refers to becoming more responsive and resilient to the unavoidable negative impacts. In line with mitigation strategies, firms, and the supply chains (SC) managing them have shifted focus to socio-environmental issues, and the concept of a sustainable supply chain (SSC) has emerged (Seuring & Müller 2008).

In this transitioning to SSC, production side mechanisms such as the low-carbon logistics network planning, green production technologies, eco-friendly materials, waste management, and eco-product design have been brought into consideration to reduce environmental impacts (Gupta & Palsule-Desai 2011). However, the role of consumption and consumer behavior has been largely ignored in the research on SC. Sustainable consumption patterns can considerably decrease the social and environmental impacts. According to the Intergovernmental Panel on Climate Change (IPCC) report, global warming caused by energy-related emissions (over the 21st century) can be contained to less than 2°C over pre-industrial levels by just switching to responsible energy consumption and changing dietary preferences (de Coninck, Babiker & Araos 2018). World Business Council for Sustainable Development stresses that changing consumer behavior towards more sustainable purchases can be accomplished throughout the supply chain (WBCSD 2008).

The exclusive purview of governments to incentivize SCs for adopting environmentally-friendly practices is not effective. However, promoting adaptive, wise, sustainable living requires a more inclusive concept of governance and collaboration between governmental and non-governmental actors, commercial and not-for-profit actors, as well as communities, societies, and even individuals. Moreover, given the emergence of the circular economy concept, encouraging the ideology of de-growth and regenerative design and steady-state economics instead of economic expansion and consumerism can be a part of mitigation plans. Thus, it is important to develop policies and mechanisms that can discourage unsustainable production and encourage people to make greener choices daily so that citizens can act as agents of change. Since production is always largely defined by consumption, as supply is driven by demand, there is an opportunity and a challenge for research that can change the consumption behavior towards green products and practices. To address this scientific challenge, in this thesis, first, a conceptual framework is proposed which links three very different areas (i) supply chain design and engineering, (ii) financial performance, accounting and economic optimization and, (ii) consumer behavior and environmental psychology. Then, decision-making tools and models are developed to implement and operationalize these insights and quantitatively assess the impact of changes in individual choices on the performance of SSCs.

1.2. Background and overview

A wide range of behaviors and choices such as adopting a vegetarian diet, taking energy conservation measures, and managing and recycling waste is considered as sustainable consumption; however, the framework of the thesis is restricted to food production-consumption, one of the key issues of sustainability. According to Peattie (2010), three main categories of food and drink, housing (e.g., domestic energy use), and transport (e.g., commuting and leisure) account for 70-80% of the overall environmental impacts of consumption. In particular, the contribution of the agro-food sector to global warming potential and eutrophication of surface water is estimated at 30% and 50%, respectively (Tukker & Jansen 2006). The emissions are mainly caused by the production process (e.g., farming energy requirements, synthetic chemicals) and consumption. Three green strategies to mitigate environmental footprints from a production perspective include organic agriculture, local sourcing and shorter food miles, and green packaging. Strategies for reducing the environmental impacts of consumption include a preference for fresh local products, consumption of organic food, and the reduction of red meat consumption (Tobler, Visschers & Siegrist 2011). Among all these, the promotion of organic food represents a form of behavior that can directly benefit both human health and preserve natural resources. Therefore, the thesis scope is further narrowed down to organic food production-consumption because of its significant impacts in transitioning toward a more sustainable sector.

1.2.1. Organic versus conventional agriculture

The dramatic growth in the world's population has tripled demand for food and led to increasing agricultural intensity. Today's intensive farming practices have largely increased the ecological footprint of food production. They provoke the unbalanced application of agrochemicals (such as synthetic fertilizers and pesticides) and overuse of fossil fuels for powering equipment. A growing number of farmers adopt this non-eco-friendly farming method to minimize the production costs and inputs, maximize the crop yield and outputs, achieve economies of scale, and eventually rise mega-farms. The organic agriculture method is introduced as a potential solution to mitigate the environmental effects of food production. This method relies on (1) biological pest controls to protect the crop from diseases as well as (2) cover crops, crop rotation, and organic fertilizers to maintain soil health and productivity. Although it is well accepted as an eco-friendly alternative to conventional farming (since synthetic fertilizers, fungicides, and pesticides are excluded from the land (Willer & Lernoud 2017)), its adoption rate is very low. According to IFOAM, less than 1.4% of farms worldwide are organic.

There are certain concerns about adopting organic farming practices, including lower yield, higher certification costs, more labor-intensive in comparison to conventional farming. Generally, organic growers need to wait longer for harvesting and may expect lower production per hectare (Seufert, Ramankutty & Foley 2012). While the input costs of organic farms are quite small, it is costly and challenging to deal with weed germination and disease pressure (Jonis et al. 2008). As chemical weeding is not allowed on the farm, a higher number of workers should be employed, adding to the costs. Thus, finding a balance between economic growth and the environmental impacts of organic farms is imperative for the future of food and agribusiness.

1.2.2. Environmental impacts of organic food

Comparing the environmental impacts of various methods of food production such as low-input, biodynamic, organic, etc. and determining the environmentally preferable ones is a controversial topic. Concerning the ecological burdens of the organic farming method, in which the application of synthetic fertilizers and pesticides is prohibited, scholars have arrived at confusing and contradictory conclusions. On the one hand, some associate organic cropping systems with enhanced soil organic matter and thus soil fertility due to a significant reduction in agricultural inputs (Markuszewska & Kubacka 2017). Organic farming is fairly dependant on internal resources rather than external auxiliary materials. As a result, the consumption of fossil resources and their associated impacts (GHG emission) can be declined considerably (Dalgaard et al., 2006). (Mondelaers, Aertsens & Van Huylenbroeck 2009). The restriction on the application of chemical fertilizers and pesticides in farms mitigates the ecotoxicity potentials (dominated by emissions to soil, ground and surface water) and promotes biodiversity (improved landscape management) (Bengtsson, Ahnström & WEIBULL 2005).

On the other hand, others undermine the overall positive assessment of the organic system and question to what extent it can improve environmental performance while more lands are required to produce the same amount of yields. Hence, the lower yields drive significantly higher land occupation per product unit (Tuomisto et al. 2012b). Moreover, the superiority of organic over conventional farming practices is argued because a relatively higher soil nutrient loss (such as ammonia emissions, nitrogen leaching, and nitrous oxide emissions) per unit of product are observed in the farms due to the application of organic fertilizers (Nemecek et al. 2011). Comparative studies on the conventional and organic production of milk and carrots have shown the higher land requirements and eutrophying emissions in organic agriculture (Cederberg & Mattsson 2000). As a result of various strategies taken for organic compound and manure management, in several organic farms, a higher value of ozone formation potential (so-called "summer smog") is noticed (Chen & Luo 2012).

From this discussion, one can conclude that the environmental performance of organic versus conventional farming varies depending on the product type, farm size, cropping pattern, study period, measurement unit, and data availability (Lee, Choe & Park 2015). Researchers advise that although there is no single best farming system, in many circumstances (depending on soil type, climate, altitude, and legislation), organic farming can be considered as the optimal system creating more output per environmental burden (Tasca, Nessi & Rigamonti 2017). It is agreed that organic crop systems perform significantly better in the impact categories of energy use, global warming emissions, and ozone-depleting emissions, in particular, those producing yields equivalent to their conventional counterparts.

1.2.3. Health impacts of organic food

Many studies report that organically produced food is healthier than conventional food due to its lower content of harmful substances (e.g., nitrate contents and pesticide residues) (Huber et al. 2011) and higher content of bioactive compounds (e.g., vitamin C and phenolic compounds) (Brantsæter et al. 2017). The application of environmental pollutants, including antibiotics (in meat and milk), pesticides (in fruits and vegetables), and heavy metals (e.g., cadmium) in the conventional cropping systems can cause gut microbiota dysbiosis and immune-related disorders (Jin et al. 2017). The prevalent use of antibiotics in commercial poultry farming methods drives antibiotic resistance in humans (Mie et al. 2017). Also, the energy metabolism of the body is indirectly affected by antibiotics in food (Rolain 2013). According to the new FDA monitoring program, almost 50% of domestic and imported food in the United States have detectable pesticide.

Pesticide residues present on food is the primary source of hazardous exposure that may cause neurotoxicity, and hepatotoxicity (Torjusen et al. 2014). Several chronic health issues such as asthma (Raanan et al. 2016), cancer (Bassil et al. 2007), infertility (Bretveld et al. 2006), autism, hyperactivity, and other cognitive-behavioral disorders (Rauh et al. 2011) are associated with exposure to low-level dietary pesticides. Another controversial issue is relevant to the health impairments observed on farmer workers. Evidently, the higher health risk is imposed on farmers, their children, and the communities living and working near pesticide-treated farmland in comparison to organic farms (Frank, Finnegan & Taylor 2004). A large number of studies confirm the adverse effects associated with occupational exposure to pesticides, raising concern for hematological, biochemical change, respiratory, neurological, genotoxicity, and cancer among workers (Dhananjayan & Ravichandran 2018; Fuhrimann et al. 2019).

Although the research on comparing the nutritional value of organic to conventional food is still ongoing, a higher level of omega-3 fatty acids in dairy products and phenophelon in vegetables and fruits has been approved (Mie et al. 2017). Several studies found a strong association between reduced risk of cancer and adopting an organic food diet (Baudry et al. 2018). Hyland et al. (2019)'s findings confirm that in the individuals that have only organic diets, the level of several pesticide metabolites and parent compounds are reduced by 60.5% in only seven days. In another survey, Di Renzo et al. (2007) observe the higher antioxidant levels in the plasma of 10 individuals after taking organic apples. A recent study by Hurtado-Barroso et al. (2019) over the impact of food on human health concludes that the high frequency of organic food consumption and organic diet can protect people against adverse health outcomes of conventional food. Therefore, cutting the application of chemicals in the farmlands can significantly reduce the adverse health impacts of conventional food on both final consumers and farmers.

1.2.4. Sustainable food consumption

Excessive use of natural resources to provide for ever-increasing irresponsible consumption of products and services in recent decades has prompted environmental degradation worldwide. Consumption patterns and consumer preferences play a role in accelerating ecological deterioration (Biswas & Roy 2015). While the rate of environmental degradation is rapidly increasing, the changes in individual behavior to more sustainable purchasing practices are much slower (Taufique & Vaithianathan 2018).

Opposed to traditional economic models that focus on optimal choice, constrained utility maximization, and pure rationality in decisions, behavioral economics discuss biases in the decision-making process (Frederiks et al., 2015; Kahneman, 2003; Stern, 1992; Wilson and Dowlatabadi, 2007). It is not only economic factors that influence individuals' green choices but also their beliefs, biases, and perceptions. In practice, a wide range of complex factors contributes to environmentally responsible purchasing and eco-conscious behavior. These factors can be generally classified as cognitive and situational factors (Joshi & Rahman 2015). Cognitive factors are derived from an individual's traits, cultural norms, subjective knowledge, and life experiences. Situational factors are related to product price, availability, substitutes, social norms, and reference groups, quality, brand image, eco-labeling, and certifications.

Behavioral change theories are used to explain the individual multi-stage process of decision-making. The most famous behavioral change theory applied in food purchasing behavior is the theory of planned behavior (TPB) (Ajzen 1985). TPB explains that a particular behavioral choice is preceded by intention, which in turn is influenced by an individual's behavioral, normative, and control beliefs. It provides an opportunity to simulate a psychological decision-making process able to consider cognitive, contextual, and social dimensions. In quantifying the influence of behavioral factors on food- related decisions, the bulk of empirical studies have deployed statistical methods. They are used to analyze observational data, draw interference, and provide models for estimating the organic food preferences of population from a sample. Recently, the application of machine learning algorithms has gained researchers' attention because of its promising performance in deriving predictive models with higher accuracy. These algorithms can efficiently deal with complex and non-linear relationships between multiple variables considering no predetermined structure.

A set of various intervention strategies targeting the promotion of a particular green behavior have been proposed by researchers (Steg & Vlek 2009). Generally, they are classified into persuasive and structural strategies. The former aims at changing the individual-cognitive factors (e.g., green concern, knowledge, personal norms), whereas the latter focuses on the situational-contextual factors motivating individuals to engage in pro-environmental behavior (e.g., price, availability, social norms). The effectiveness of these strategies in orienting people's behavior towards greenness depends on the characteristics, motivation, regional culture, and situation of different target groups. Several quantitative/computational methods of analysis find their common ground to assess the extent to which interventions provoke sustainable behavior change. System dynamics modeling (SD) is the earliest employed method in computational social science that takes into account aggregated variables to describe the complexity. Later, agent-based modeling (ABM) is developed and applied in studies to simulate the individual behavior of social actors as autonomous agents. These heterogeneous and adaptive agents are not perfectly rational. Their decisions are continuously influenced by their dynamic interactions with the other and the environment (Jager & Ernst 2017a). The collective actions of agents at the micro-level over a prolonged period of time can lead to emerging outcomes at the macro-level. In turn, macro-level actions can feedback into the actions of micro agents. The superiority of ABM over the field experiment approach lies in its experimental power and lower costs.

1.2.5. Australian organic food market

The organic agriculture sector has witnessed popularity and economic growth in the mid-1990s when the certified organic farms have substantially expanded due to the increasing demand of retailers for natural and eco-friendly food products (Chen & O'Mahony 2013). Recent reports show an exponential increase in global organic land area from 11 million hectares in 1999 to 70 million hectares in 2018 (Luttikholt et al. 2019). The area of agricultural land under certified organic management in Australia is 35 million hectares, the largest area in the world (Lawson, Cosby, Baker, Leu, et al. 2018). The global sale records show that organic food sales had surged from $US 15.2 billion in 1999 to more than $100 billion in 2018. Currently, the United States (US) and Europe make up 90% of global retail sales. The US is leading the organic food market with a total sales of $US 52.5 billion in 2019. European organic market is represented by Germany 30%, France 18%, the United Kingdom 9% (Willer & Lernoud, 2016). The highest per capita consumption of organic belongs to Switzerland, Denmark, and Sweden, ranging from $US 175 to $US 250 (Nechaev, Mikhailushkin & Alieva 2018).

The recent report by the Australian organic market report (2018) indicates overall growth in the Australian organic market from $US 20 million in 1990 to $US 1,143 million in 2017 (Lawson, Cosby, Baker, Leu, et al. 2018). However, the value of this market is mainly appraised by the rapidly growing demand in the global market. While the domestic rate of demand for organic products has gradually increased, it is far less than the rate as the conventional products and the overseas demand rate for Australian organic products. The Australian estimated per capita consumption of organic food is about US$ 20. This value shows that Australians are set out from the top ten countries with the highest per capita consumption of organic products. Clearly, there is a gap between the production and consumption of organic food, and the sector has room to grow in Australia.

1.2.6. Australian wine sector

Since the introduction of chemicals in the 19th century, viticulture has significantly contributed to a wide range of environmental issues, particularly those related to land and water pollution. By excluding agrochemicals from vineyards, organic agriculture helps to preserve biodiversity and the overall quality of agroecosystems (Rugani et al. 2013). Organic agriculture contributes to the mitigation of the environmental burdens of wine production by excluding agrochemicals from vineyards (Provost & Pedneault 2016).

The Australian wine industry is comprised of over 6,000 vineyards, approximately 2,500 winemakers, and more than 175,000 people contributing $AU 40 billion to the economy annually. In 2018, 135,000 hectares of land across the country, mainly in Southern Australia, is used to produce 1.29 billion liter wine, most of which (around 65%) are exported at $AU 2.8 billion. The primary driver of wine demand is export markets, including China ($AU 1.14 billion), the United States ($AU 425 million), the United Kingdom ($389 million), Canada ($AU 210 million) and New Zealand ($AU 93 million) (Australian Competition and Consumer Commission, 2019). Figure 1.1 presents the dynamics of wine production and exports from 1990 to 2018. While the international sales volume has increased over the last decade, the domestic sales volume has remained constant.

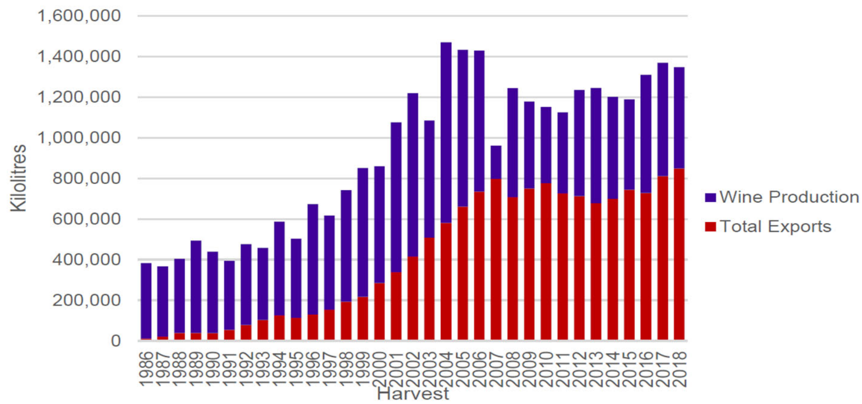

Figure 1.1. Australian wine production and wine exports by year (Danenberg 2018).

A variety of wine grapes with a considerably distinct price and quality are produced in cool and warm climate regions. The price of grapes in the cool climate regions (e.g., Hunter, great southern region, etc.) goes beyond $AU 8,000 per tonne, and the average yield varies between 3 and 13 tonnes per hectare. Whereas the price of warm climate (e.g., Riverland, Murray Valley, etc.) grapes is significantly lower, less than $AU 300 per tonne, and the yield is dramatically higher, varying between 20 and 30 tonnes per hectare (Australian Competition and Consumer Commission 2019b).

Currently, less than 0.5% of grape production volume in the Australian wine market belongs to organic wine and the total global organic vine area reached 400,000 hectare in 2017 (Wine Australia 2017). Most of the certified organic wines are exported to Europe (78%, including Sweden, UK) and the United States (12%). According to a recent report of Wine Australia (2019), the percentage of Australians "sought to purchase any organic wine in the past six months" is approximated at 20%. Despite the growing interest in the global market, still, organic wine remains a niche segment in the domestic market.

1.3. Research goals and challenges

The main research challenges to be addressed in this thesis are discussed below.

1. Addressing sustainability in the supply chain using demand-side strategies:

   Sustainability and SC research are difficult to marry. Since sustainability is largely a social concept and after all, the natural and especially the economic function of systems is important only for the sake of social benefits, it makes little sense to analyze SSC unless they include the social systems that they interact with. Thus, considering the consumers and their preferences for green products is of utmost importance in the management of SC. Since there are usually additional costs of sustainable practices, green products tend to be more expensive than conventional products (Nidumolu, Prahalad & Rangaswami 2009). Therefore, if consumers have no awareness of the advantages of green products and their willingness to pay for them is not stimulated, there will be no incentives for SCs to adopt green practices.

2. Understanding consumer behavior towards the purchase of organic food and exploring the long-term effects of interventions on changing their preferences:

   It is challenging to understand the decision-making process and explore the key stimuli that lead people to make choices between organic and non-organic food in the complex shopping environment. So far, experimental statistical studies have been conducted to help researchers in examining the organic versus non-organic food choice of consumers. Yet, they could not provide a clear understanding of the extent of interventions that can influence the behavior of consumers. Several limitations stem from using statistical approaches. Firstly, running an experiment can take considerable time, costs, and effort before reaching the desired results, if reaching them at all. Secondly, empirical data alone hardly provides information about the implications of food consumption reasoning for the patterns that are seen on the regional and national levels. Thirdly, consumers are not making decisions in isolation, and they are prone to the influence of interactions with peers in their social networks and local communities. Fourthly, the effectiveness of designed interventions has to be monitored over extended periods, while experimental assessments fail to consider long-term effects. These limitations emphasize the need for methods that complement the empirical information about the complexity of food purchasing decisions.

3. Evaluating the impact of changing organic food consumption patterns on the sustainable performance of agro-food supply chain:

   So far, sustainable agro-food SC models focus on production-side mitigation strategies for reducing environmental footprints. These strategies are mainly relevant to the low-carbon transportation network, local sourcing and food miles, as well as advanced processing technologies and green packaging. However, improving production systems alone may not bring considerable emission savings to the agro-food sector if not accompanied by consumption-side strategies. Demand-Side solutions, especially consumer preferences for sustainable food products and their influence on the configuration of the SC has been left out of consideration from the SSC models. Literature analysis shows that none of the developed models have addressed the issues related to the dynamics of willingness to pay more for organic food, the demand substitutions, and organic versus conventional land management decisions, simultaneously. The complexity of the relationships and the uncertainties involved in the characteristics of agro-food products increase the sophistication of implementing such a comprehensive model.

4. Investigating the gap between consumers' intention and behavior for purchasing organic food:

   Prior studies have reported various behavioral factors as key drivers of consumers' intention for purchasing organic wine. Yet only a few examined the differences between intention and real purchasing behavior for organic wine. According to the literature on consumer behavior, a combination of cognitive and affective factors may interrupt the intention-behavior relationship. We emphasize on the importance of impulsive and unplanned purchasing behavior, which currently are disregarded from the organic food purchasing studies. In particular, there is a lack of research on the influence of non-cognitive variables of emotions, impulse tendency, and personal goals on the consumer choice for organic products. Moreover, statistical methods are the dominant in providing models for predicting the consumers' wine purchasing behavior. While these methods can successfully reveal the relationship between the variables, their predictive power and accuracy as opposed to machine learning algorithms are low. These theoretical and methodological gaps require further attention and consideration to better understand the heterogeneity in consumers and their organic purchasing behavior.

1.4. Objectives, and research questions

To attain the goals outlined above we are focusing on the following four research objectives and twelve research questions:

1. To conceptualize the idea of extending supply chain analysis to consumers and their green behavior by developing a comprehensive conceptual framework.

    a) What strategies have been taken in SC literature for addressing sustainability issues?

    b) What impacts do taking sustainability initiatives have on the economic and environmental performance of SSCs?

    c) Can changing consumers' preferences and behavior towards green products address the sustainability issues in SC?

2. To simulate consumer purchase decisions for organic food and quantify the influence of different behavior change interventions on changing their food preferences by developing an agent-based model.

    a) Can behavioral theories help us to estimate consumers' decision making process for organic wine?

    b) What interventions may be effective in changing the preference of conventional wine consumers towards organic wine?

    c) To what extent these interventions can trigger the transition towards organic wine adoption?

3. To quantitatively assess the impacts of changing consumer behavior on the economic, environmental, and social performance of agro-food SC by developing an integrated model for a wine SC case study.

    a) How to integrate the heterogeneity of consumers, dynamics of supply-demand relationship, and changing expectations of farmers into traditional SSC for agro-food ?

    b) Which modeling techniques allow us to simulate the operation of autonomous actors of ESSC - from farmers, to processors, retailers, and consumers?

c) What impacts do probable changes in consumers' economic status and social networks have on the performance of ESSC in terms of sustainability indicators?

4. To empirically assess the relative importance of affective factors -emotions, impulse tendency, personal goals - as well as cognitive factors - attitude, PBC, habits and social norms - on organic wine purchasing decisions using survey data and machine learning approach.

   a) What behavioral theories can conceptualize the decision making process in individuals with regards to organic wine?

   b) How to derive predictive models for estimating consumers' intention and behavior for purchasing organic wine with high accuracy from empirical data?

   c) What are the differences and similarities between different segments of organic wine consumers?

1.5. Research contributions

The proposed work has led to the following contributions.

1. A new conceptual framework, the Extended Sustainable Supply Chain, is proposed to emphasize the importance of consumers and their green behavior for sustainability features of supply chains. To the best of our understanding, this is the first study that systematically integrated demand-side mitigation strategies with the producer-side. While it is understood that focal firms should contribute to identifying possible strategies for motivating the pro-environmental behavior of stakeholders, particularly consumers, SSC studies stop short from embedding consumers and their behavior into analyses. From a theoretical perspective, for transitioning towards sustainability, it is crucial to take the extended supply chain view, in which the boundaries of analysis are expanded to include consumers and their behavior. From a managerial perspective, the framework explains how the financial risk of moving towards SSC can be mitigated through increasing the market share of green products and investing in consumer awareness and acceptance campaigns.

2. A behavioral model, ORVin, is developed to advance knowledge about the effectiveness of behavior change policy instruments by explicitly considering consumer perceptions and preferences for organic products. Within the scarce modeling literature on behavioral change towards sustainable food, this is the first simulation model proposed to understand bottom-up choices between organic and non-organic wine and the policies that can impact them. Moreover, in this model, we explicitly trace the effects of social interactions, drinking habits, and desirability factors on wine consumption behavior. Previously, social norms have not been considered as a factor for wine purchasing behavior, yet they strongly influence how consumers choose organic wine.

3. A novel integrated simulation model is designed to bring about the principals of the ESSC framework, where the scope of SC analysis is extended from the production operations to consider the buying behavior of consumers. The model links three very different areas that, to our knowledge, have not yet been synthesized into an analytical study: (i) supply chain design and production economy, (ii) socio-environmental assessment and, (ii) consumer behavior and environmental psychology. While several researchers empirically examine consumer preference for sustainable food, we are not aware of any published studies that analytically link the behavioral aspects of consumption to production. Moreover, to the best of our knowledge, this is the first study that incorporates the preferences of consumers for organic food as well as farmer decisions regarding organic farming adoption into the modeling of the food SC.

4. A new empirical study on examining the interplay between cognitive and affective factors in purchasing behavior for organic food. To our knowledge, there has been no quantitative, generalizable study considering the emotions, impulse tendencies, and personal goals as factors interrupting the relationship between intention and behavior for purchasing organic wine. The literature of organic wine purchasing mainly focuses on planned behavior, yet the impulsive and unplanned behavior can greatly influence the shopping decisions.

5. This study contributes to the methodological development in operations research by proposing an integrated simulation methods - agent-based modeling, discrete event simulation, and system dynamics modeling - to investigate the influence of decisions on the performance of the SC in the long run. The literature highlights that the SC field is dominant by optimization methods, and systems thinking approaches are underrepresented. SSC field can benefit from an integrated

modeling solution that simulates the interplay between SC and socio-environmental conditions and at the same time explore optimal scenarios for improving the situation. The novelty of our model lies in presenting the simultaneous interactions between different SC echelons (defined as adaptive systems)- farmers, processors, retailers, and consumers - at different spatial and temporal scales. In doing so, we provide new insights into how simulation can pave the way towards understanding consumer preferences and their influence on the choice of farmers for land management, processors production schemes, retailers pricing strategies.

6. This study advances the methodological principles of empirical wine studies by applying both unsupervised and supervised machine learning algorithms to survey data. In our literature survey, we could not find any study employing machine learning to derive models for making predictions of wine consumer behavior. This improves the predictive power of data-driven models in estimating the future organic wine preferences of individuals and provides new insights on different consumer segments and the importance of factors on the wine related decisions.

1.6. Outline of the thesis

The dissertation consists of six chapters. Apart from the introduction and conclusion, three chapters address the primary goal of the thesis systematically, as shown in Figure 1.2. Each chapter deals with one or two specific research question(s):

Chapter 1 presents an overview of the motivation, the background, research questions, and the scientific challenge of the dissertation.

Chapter 2 introduces a broad review of the evolution of sustainable supply chain literature and a novel conceptual framework for addressing sustainability issues of SCs.

Chapter 3 proposes a model for examining consumer purchasing decisions for organic food and assessing the effectiveness of behavioral change interventions.

Chapter 4 evaluates the cumulative impact of changing consumer behavior for organic food on the decisions of the agro-food supply chain and its sustainable performance by introducing an adaptive supply chain model.

Chapter 5 outlines the main determinants (including demographics, behavioral, and drinking style factors) of individuals' intention and behavior for purchasing organic wine by analyzing consumers' survey data.

Chapter 6 synthesizes the main findings and suggests future research directions.

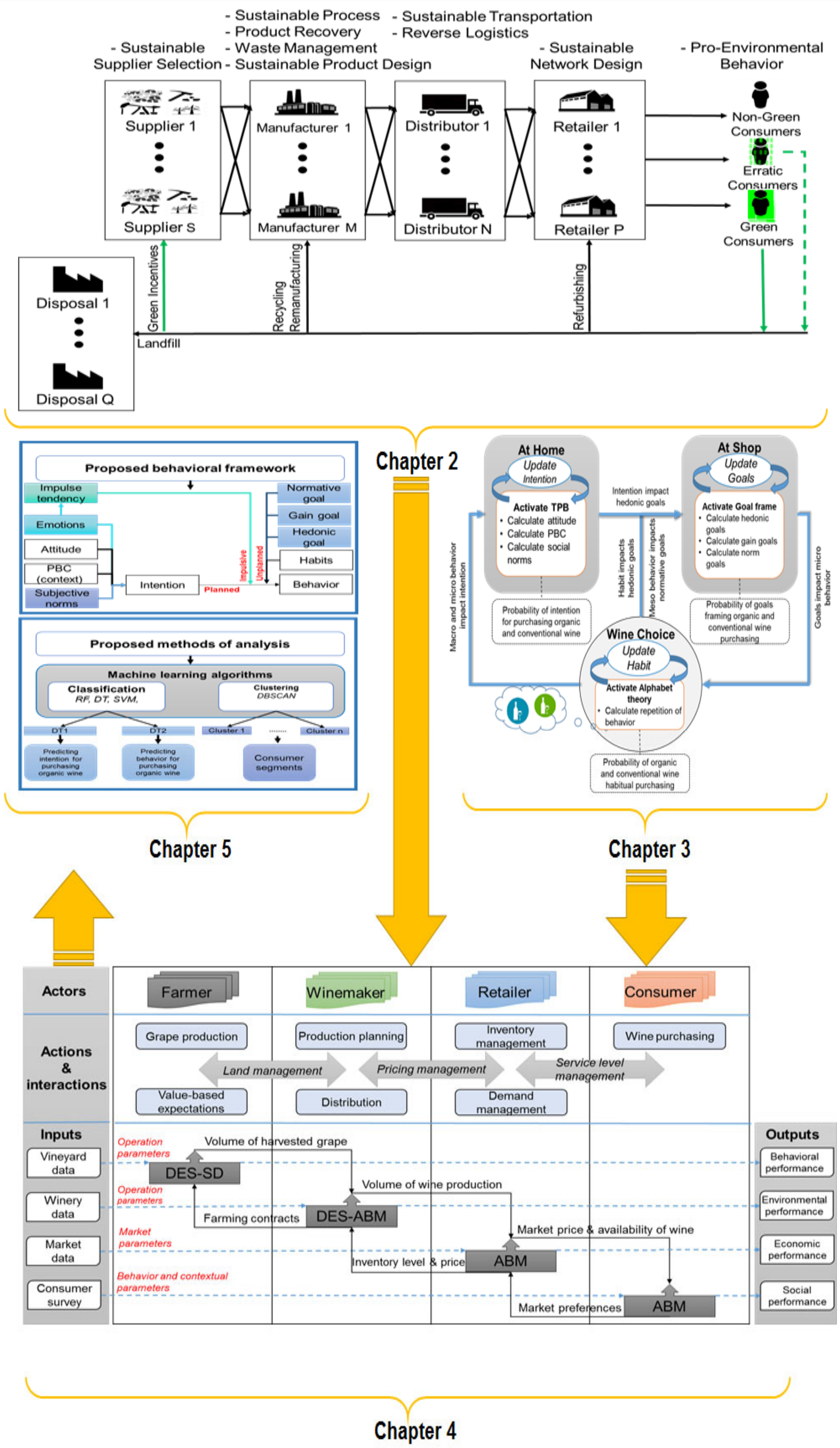

Figure 1.2. Outline of the dissertation

Chapter 2:

Extending the Supply Chain to Address Sustainability

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Abstract

In today's growing economy, overconsumption and overproduction have accelerated environmental deterioration worldwide. Consumers, through unsustainable consumption patterns, and producers, through production based on traditional resource depleting practices, have contributed significantly to the socio-environmental problems. Consumers and producers are linked by supply chains, and as sustainability became seen as a way to reverse socio-environmental degradation, it has also started to be introduced in research on supply chains. We look at the evolution of research on sustainable supply chains and show that it is still largely focused on the processes and networks that take place between the producer and the consumer, hardly taking into account consumer behavior and its influence on the performance of the producer and the supply chain itself. We conclude that we cannot be talking about sustainability, without extending the supply chains to account for consumers' behavior and their influence on the overall system performance. A conceptual framework is proposed to explain how supply chains can become sustainable and improve their economic and socio-environmental performance by motivating consumer behavior toward green consumption patterns, which, in turn, motivate producers and suppliers to change their operations.

2.1. Introduction

Traditionally, profit enhancement and cost leadership were the primary focus of supply chain (SC) management (SCM). However, more recently, the increasing rate of environmental degradation and resource depletion caused by economic growth have shifted focus to socio-environmental issues, which in the context of SC research led to more concern about sustainability, and the concept of a Sustainable Supply Chain (SSC) has emerged. At first, SSCs were to consider economic, environmental and social concerns in all activities along the supply chain, from the point of origin to the point of consumption. Later, this was supplemented by ideas of reuse and recycling borrowed from the circular economy concepts. In Circular Supply Chains (CSC) sustainability was to be a concern over the entire value chain, from cradle to grave. In this transitioning to SSC and then to CSC, the issues of logistics network planning based on green initiatives, green production and inventory management, waste management and eco-product design have been brought into consideration.

However, the role of consumption, and consumer behavior has been largely ignored in the literature on SC. Sustainable consumption or green consumer behavior refers to customers' choice not to purchase and use environmentally harmful products, and instead consume products that benefit the environment (Elkington & Hailes 1988; Steg & Vlek 2009). Sustainable consumption patterns can considerably decrease the social and environmental impacts (Steg & Vlek 2009). According to the Intergovernmental Panel on Climate Change (IPCC) report, global warming caused by energy-related emissions (over the 21st century) can be contained to less than 2°C over pre-industrial levels by just switching to responsible energy consumption and changing dietary preferences (IPCC 2015). World Business Council for Sustainable Development stressed that changing consumer behavior towards more sustainable purchases can be accomplished throughout the supply chain (Mead 2018). Supply chains are responsible for encouraging pro-environmental behavior of customers and their willingness to pay for the green premiums. Since there are usually additional costs of sustainable practices, green products tend to be more expensive than conventional products (Nidumolu, Prahalad & Rangaswami 2009). Thus, if consumers have no awareness of the advantages of green products, they may be not willing to pay for them, and there will be no incentives for supply chains to adopt green practices.

Almost five years ago, Pagell & Shevchenko (2014) have noticed that sustainability and SC research are difficult to marry and expressed huge concerns about the future of research on sustainable SC. They have suggested that “Future SCM research will have to treat a supply chain’s social and environmental performance as equally or more valid than economic performance.” Clearly, this was not and hardly is happening. As a solution Pagell & Shevchenko (2014) proposed changes in norms, measurement, methods, and research questions. Some of this resonates with the current proposals of developing SC in ways that would resemble how natural systems work (Gruner & Power 2017). We think that since sustainability is largely a social concept (since after all, the natural and especially the economic function of systems is important only for the sake of social benefits (Voinov 2017)), it makes little sense to analyze SSC unless they include the social systems that they interact with.

In this paper, we argue that - to be successful in operationalizing sustainability in the context of SC, consumer behavior has to be considered as part of the SC analysis. We propose a conceptual framework, the “extended sustainable supply chain” (ESSC), in which the relationship between buying behavior of consumers and SSC operation is considered. We argue that by motivating sustainable consumer behavior, we can, in turn, drive the decisions along the whole SC, also influencing the production process. The key message of ESSC is that producing and consuming can both become more responsible and sustainable if behavioral as well as operational aspects are taken into account.

From the theoretical perspective, we highlight the holistic view of sustainability goals in SSC and emphasize the role of consumption patterns in SC operation. From the managerial perspective, this study explains how the financial risk of moving towards SSC can be mitigated through increasing the market share of green products and investing in consumer awareness and acceptance campaigns. We offer several examples of SC where management focused on modifying consumer preferences toward more sustainable products and SC operations. This in turn increased the overall profitability of the SC. In this paper, we start with a broad review of the evolution of sustainable supply chain literature. The proposed conceptual framework of ESSC is presented in section 2.3. The implications and conclusions are discussed in section 2.4.

2.2. Evolving view on sustainability in supply chains

There are quite a few recent literature reviews available on sustainable and green supply chains. For e.g. Govindan, Soleimani & Kannan (2015), Ansari & Kant (2017), Barbosa-Póvoa, da Silva & Carvalho (2017), Bastas & Liyanage (2018) and Koberg & Longoni (2018). In this paper, we focus on the evolution of the SSC concept in literature to show how it was gradually embracing additional ideas and mechanisms relevant to sustainability, while stopping short of including the consumer behavior into the picture. Some of the most important papers in this area include publications by White & Lee (2009), who discussed a framework for integration of social sustainability in SSC analytical approaches, Jaehn (2016), who gave an overview of sustainable operations, Stindt (2017), who described a general framework for decision-making in SSC, and Gaur et al. (2016), who presented an overview of behavioral and operational aspects of waste collection and reverse logistics. Logistics and transportation, network design, production operation and product design are the most discussed topics in the SSC context. While there are hundreds of papers published in this area, here we mention only the most relevant ones as illustrations for each topic, for each category of SC analyses in the typology that we have identified. They are critically compared and contrasted so that the gap of what still needs to be known and researched can be identified.

Scientific databases such as Scopus and ScienceDirect were used to search for relevant papers containing keywords such as “sustainable” or “green” together with “supply chain” and “closed-loop supply chain” within their title, abstract, or keywords.

2.2.1. Traditional supply chain

With the emergence of globalization, most small and large organizations have realized the need for intercontinental integration to compete in the global market. The goals of gaining competitive advantage and reducing business costs could be reached only through extensive cooperation and expansion beyond national boundaries and into other continents. Supply chain research has emerged as a modern commerce solution to leverage this shift to the networked economy (Tseng & Hung 2014). The supply chain term, initially defined by Oliver & Webber (1982), refers to the systematic collaboration between people, processes, and information of alike organizations to create tangible (i.e., product) or intangible (i.e., service) values and deliver them to the customers. In this regard, supply chain management evaluates and aligns end-to-end business processes with the market demand to create competitive advantage over the rivals, while it does not consider how the demand is generated.

In the digital age, more complexity could be afforded when analyzing supply chains which changed its management perspective to accommodate flexibility, agility, and adaptability. This broader perspective implies the need for extending the supply chain objective from overall supply chain cost reduction to operational efficiency improvement. Aligned with this change, the primary focus of research papers on supply chains shifted from pure economic goals to operational goals (Goetschalcks & Fleischmann 2008). Reducing the total costs of supply chain operation, increasing the total income, and eliminating the asset's exposure to risk are some examples of financial goals supply chains sought to attain in the long-term (Goetschalcks & Fleischmann 2008; Stadtler 2008). To survive in increasingly competitive business environment, competitive strategy formulation could assist supply chains in gaining market leadership and maximizing the return on investment (Giunipero, Hooker & Denslow 2012). Time management, an important element in operation efficiency, and a source of competitive advantage, was the focus of supply chain studies for a long time. Following the time-based strategy, new technologies, based on highly-automated systems, and high-speed communication routes were developed to shorten delivery time of orders. Enhancing customer services, upgrading the quality of products, product customization, and building resilience were the other examined strategies for gaining competitive results (Christopher 2016).

To achieve the determined competitive strategies, the core business functions of supply chains including transportation and logistics, manufacturing and service, and procurement were to be re-evaluated and re-designed (Mentzer et al. 2001). Many avenues of research on supplier selection and management, production planning and process optimization, logistics and distribution, transportation selection, workforce scheduling, resilience and risk assessment, finance and accounting have been developed for supply chain management (Kouvelis, Chambers & Wang 2006). Figure 2.1 represents the major players involved in traditional supply chains. Analyses of how exactly the materials were produced and supplied and how the products were used by the customers was beyond the boundaries of supply chain research.

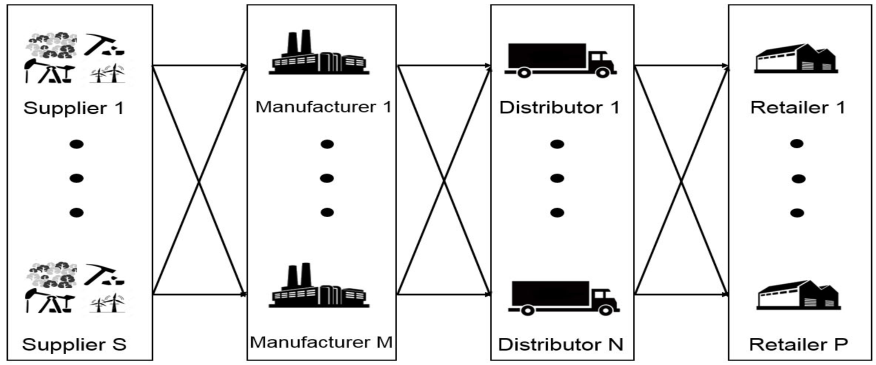

Figure 2.1. Major players of a traditional supply chain

2.2.2. Sustainable supply chain

Throughout the human history, deforestation, loss of soil fertility, and water shortage have been ever-growing ecological issues resulting from farming, mining and other human practices (Du Pisani 2006). Maintaining the "everlasting youth" of the earth or what we today call "sustainability" was a matter of discussion since the 5th century. Sustainability as a term had first appeared in the German forestry industry in 1713 when there was a shortage of wood supply in Europe. This promoted forest conservation, preservation and tree planting programs (Du Pisani 2006). Concerns about population growth, uncontrolled industrial and economic growth, and non-renewable resource depletion increased following the first oil crisis of 1973 (Du Pisani 2006). Evolving over the years, sustainability has been discussed in various contexts and was presented in a number of ways to draw the attention to the environmental issues and the necessity to take serious actions. Most studies in Sustainable Supply Chain (SSC) literature were developed based on Brundtland commission definition for sustainability as meeting the needs of today without compromising the ability to meet the needs of the future generations (WCED 1987). While there are serious concerns about the meaning of this definition and vagueness about what present and future needs are, and what should be sustained (Voinov 2017), the Brundtland report was pivotal to introduce the ideas of sustainable development to the political process.

Today, the challenge of sustainability is among the top 10 unresolved global concerns and still draws much attention (Global Agenda Council on Climate Change 2018). To address this concern, legislatures and governments, issued environmental laws describing a set of preventive-protective policies, regulations, and procedures (Ageron, Gunasekaran & Spalanzani 2012). The environmental laws accompanied by the societal norms and values, the stakeholders' awareness, and organizational culture, directly and indirectly, affected the management strategies of many businesses. Environmental impacts related to the supply chains in most sectors are considered to be increasingly important for sustainable development. Under external and internal pressures, businesses decide whether they want to change taking into account environmental concerns, and if so what changes should be made in their supply chains. SSC is the incorporation of socio-environmental sustainability goals into the systematic arrangement of key inter-business functions along a chain. It was seen as a potential solution to improve the sustainability performance in the long-term (Carter & Rogers 2008).

A number of terms such as green supply chain (Srivastava 2007), low-carbon supply chain (Shaw et al. 2012), social supply chain (Hutchins & Sutherland 2008) and ethical supply chain (Seuring & Müller 2008) can be found in the SSC literature. Green supply chain referred to the idea of synchronizing green thinking with sourcing raw materials, producing a product and delivering it to the final customer to gain competitive advantage in terms of environmental sustainability (Srivastava 2007). Social supply chain, on the other hand, was the term used for supply chains that made a trade-off between their economic goals and social responsibilities to improve their shared values with stakeholders (Porter & Kramer 2011). SSC was associated with the application of the triple bottom line indicators, a well-established sustainability framework, to supply chains (Gimenez, Sierra & Rodon 2012). SSC encompassed three distinct economic, environmental and social dimensions for sustainability. The competitive advantage of SSC can be achieved in the intersection of these dimensions (Elkington 2013). However, the challenge of integrating different sustainability performance was yet to be addressed (Ansari & Kant 2017).

For transitioning to sustainability, managers revisited their current operations and identified opportunities for mitigating the relevant impacts in specific areas within supply chains (Brandenburg & Rebs 2015). Logistics arose as the primary environmentally and socially sensitive operation in supply chains. Many papers focused on different aspects of logistics including transportation, distribution, and network design to decrease the stress on ecology and society for long-term viability (Brandenburg et al. 2014; Fahimnia, Sarkis & Davarzani 2015). More specifically, the environmental values (e.g., the reduction of carbon emissions, energy consumption) and social values (e.g., welfare of society, labor condition, and ethical practices) were incorporated into the evaluation, selection, and design of logistic networks.

Consider, for example, the **transportation mode** problem in logistics as it significantly contributes to the issue of climate change. According to World Bank (2014), 20% of the World carbon dioxide (CO_2) emissions were generated from transportation and logistics. Almost all primary modes of transport have harmful environmental impacts. Sustainable logistics studies are continuously looking for green modes of transportation to decrease their carbon and energy footprints. One way is to facilitate the use of environmentally-friendly transport such as trains and ships/barges to decrease emissions (Jaehn 2016). These transportation modes have been less popular in supply chains. The low utilization rate of low-impact transport was mainly related to the issue of poor accessibility. To address this issue, intermodal transportation studies have been conducted in order to combine the most eco-friendly modes and give easy access to customers (Kirschstein & Meisel 2015). Shared/ joint transport was another way for decreasing the environmental impacts by intensifying use of vehicles or by ride-sharing. In joint transportation, a supply chain may decide whether to join another supply chain transport, so that the logistic costs can be redistributed among the partners (depending on the cost-sharing agreement) and the total emissions would be reduced (Boyacı, Zografos & Geroliminis 2015).

Vehicle routing is another way to reduce environmental impacts. The routes for a fleet of vehicles could be optimized with regard to costs and emissions. The emission reduction goal for route selection was pursued through minimizing the energy/fuel consumption (Bektaş, Demir & Laporte 2016). The rate of fuel consumption, in turn, was determined by various factors including the travel distance and speed (Demir, Bektaş & Laporte 2014; Osmani & Zhang 2017), travel time, and the number and type of vehicles used (Lin et al. 2014). The integration of emissions reduction goals in vehicle routing can backfire, when rerouting results in more traffic, higher fuel consumption and emissions (Jaehn 2016). Furthermore, the harmful impacts of vehicle routing may cause other environmental impacts such as noise pollution or increase in impervious surfaces created by new roads. The electric fleet routing problem as an alternative option to deal with environmental pollution has attracted much attention in SSC logistics (Hiermann et al. 2016). The challenges of electric vehicle/fleet such as the long recharging times (Chung & Kwon 2015; Eberle & Von Helmolt 2010), smaller capacities (Richardson 2013), and limited availability of recharging stations (Desaulniers et al. 2016) were studied by a number of researchers. Although electric fleet can decrease pollution, the environmental impact of their batteries and generation of electricity have raised many concerns. The social aspects of transportation were rarely incorporated into SSC studies. Providing goods and services to people in remote areas, giving quicker accessibility to central facilities (e.g., schools, hospitals), noise pollution and accidents caused by traffic were rarely cited by scholars. Overall, it should be noted that in all these cases the 'sustainability' or 'greening' of the SC was usually well connected to overall economic efficiency of the operations.

Sustainability issues became also important in logistics **network design** where social sustainability was given considerable importance. This branch of logistics was about determining the optimal location for one or more facilities to meet various, perhaps conflicting, demands. To find a suitable location, a set of potential sites for facilities were pre-selected and ranked with regards to economic, environmental and social considerations. Then, the spatial locations of all the other available facilities involved in the supply chain were identified. Finally, the desired number and location of new facilities were determined such that adverse impacts were minimized and the customer demands were satisfied. The optimal production allocation to different facilities and the optimal distribution of commodities from facilities to customers with regard sustainability objectives (e.g., cost reduction, ecological benefit, and public accessibility) were considered in several papers (Eskandarpour et al. 2015). Most SSC network design studies aimed at minimizing the ecological impacts (e.g., reducing emissions) through minimizing transportation (Bouzembrak et al. 2013; Zhang, Wiegmans & Tavasszy 2013); nevertheless, there were studies considering the environmental impacts of facilities as well, by examining their energy efficiencies (Devika, Jafarian & Nourbakhsh 2014; Govindan et al. 2014).

We can argue that these types of SSC had a strong flavor of 'green-washing', since optimizing transport, routing and networks was actually also a way to improve the conventional profitability of the operations. The fact that some greenhouse gases could be also saved came as a nice complementary factor, which could be further used for publicity purposes.

Regarding the social aspects, the employment indicator was often considered in SSC studies. Employment can be measured, for instance, as the total number of jobs created (Osmani & Zhang 2017; Santibañez-Aguilar et al. 2014), the total number of variable and fixed jobs created (Mota et al. 2015; You et al. 2012), total number of created jobs in less developed regions (Varsei & Polyakovskiy 2017; Zhalechian et al. 2016), or the number of new employees in the local economy (Miret et al. 2016). Safety, another frequently used indicator is quantified by accounting for the injury rate (Bouchery et al. 2012), the number of working hours in every facility, and the health and safety index of work environment (Santibañez-Aguilar et al. 2013). In some cases, indicators were used to assess two or more social factors at the same time. For example, Dehghanian & Mansour (2009) used a multi-criteria decision making approach to weight and integrate employment, damage to workers, product risk, and local development criteria into a single social indicator. Similarly, Devika, Jafarian & Nourbakhsh (2014) aggregated indicators of employment and safety in one to assess the social impacts of designed network. Social objectives such as accessibility to goods and services (e.g., food), equality in access to public utilities (e.g., healthcare, schools) (Beheshtifar & Alimoahmmadi 2015) and the risk of exposure to chemical and toxic wastes (Pishvaee, Razmi & Torabi 2012) (for product and facility) were rarely mentioned in the SSC literature. A summary of topics discussed in SSC is presented in Figure 2.2.

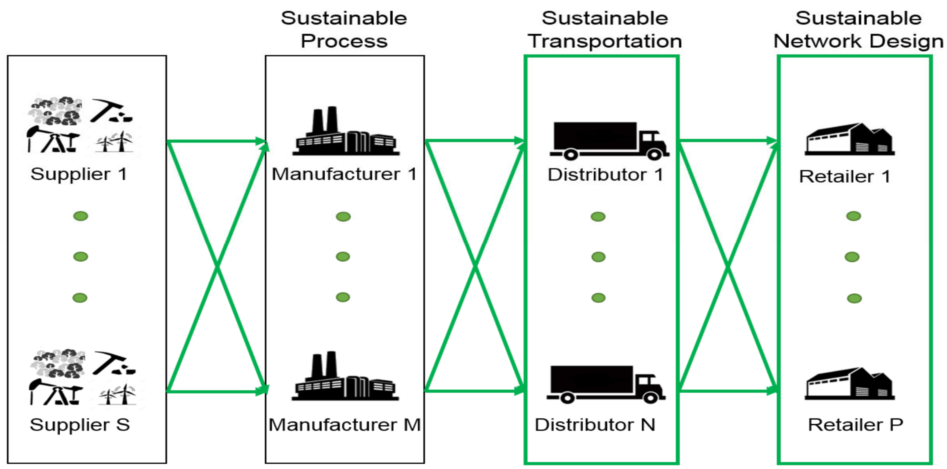

Figure 2.2. Scope of sustainable supply chain

2.2.3. Circular economy and sustainable supply chain

As we go deeper in analyzing sustainability performance, we realize that obtaining sustainable outcomes should be considered through extending producer responsibility (Mena, Humphries & Choi 2013; Vachon & Klassen 2006). It was suggested that the responsibilities of producers for dealing with sustainability issues should not end once the products are sold to customers. There should be some accountability for impacts of products during consumption and in post-consumption phase and therefore waste and 'end-of-life' management programs should be adopted. As such, the linear paradigm of supply chain has changed to a circular one.

Circular economy concept is being considered as a potential solution to address sustainable development challenges, improving the economic-environmental productivity ratio of business systems by decreasing the inputs rather than increasing the outputs (Geissdoerfer et al. 2017). The integration of the circular economy concept into the supply chain became known as “circular supply chain” (CSC) or “closed-loop supply chain.” Both terms appear in literature and are used interchangeably in this paper. Input materials into the CSC are reduced since some of the generated wastes are retrieved to be used again as resources. Thus, the energy and resource dependencies could be reduced without influencing the development and growth of the operations (Geissdoerfer et al. 2018). In fact, CSCs operationalize circular economy concept through slowing, narrowing, intensifying and closing resource loops (Bocken et al. 2016). As the management of CSC does not terminate at the point of sale, reverse logistics and waste management should be examined in coordination with the functional areas of forward logistics.

In **reverse logistics**, the closing loop of supply chains provides a feedback flow from the point of consumption to the point of origin to return items after they served their original purpose. In particular, non-functional products and waste are collected from their typical final destination for the purpose of recapturing values through reusing, remanufacturing, and recycling (Gaur et al. 2016). Though recovering or recycling the end of life products turn out to be eco-friendly activities, the energy intensity and pollution generation of backward transportation and treatment facilities should be considered. The transportation planning and network design problems in reverse logistics were very much the same as the forward logistics. However, the risks and uncertainties involved in quantity, frequency and quality of collected products make these problems more complex (Govindan, Soleimani & Kannan 2015).

The collected end-of-life items can be sorted for recovery purposes depending on the type of materials used. **Product recovery** refers to recapturing value from damaged products, seasonal inventory, recalled items, and end-of-life products. The condition of returns determines whether they are suitable for repair/reuse, refurbishing, or remanufacturing. Repair-reuse is the most forward-thinking approach preventing extra costs of treatment. Due to their waste preventing nature, this approach should be given priority in the product recovery hierarchy. In refurbishing and remanufacturing, the defects of the returned product are repaired or replaced with new components resulting in a relatively lower quality product with a lower price. The challenges of product recovery problems are mainly concerned with predicting the quantity (Clottey, Benton Jr & Srivastava 2012), quality and deciding on optimum prices and production rates for remanufactured/refurbished products (Bulmuş, Zhu & Teunter 2014; Xiong et al. 2013).

As a part of the reverse logistics process, **waste management** is also committed to sustainability objectives. Waste management problem raises the questions of which disposing option including recycling, incineration or landfill should be selected for each type of waste and where to locate the corresponding facilities. Recycling at end-of-life meets the raw material requirements of new products and thus adds sustainability value to the chain. Incineration and landfill, while perhaps economically more profitable, are non-value adding approaches that can be utilized as the last solution. In waste management problem, issues such as the allocation of waste flow (Battarra, Erdoğan & Vigo 2014), the routing of collection vehicles (Benjamin & Beasley 2010), and the scheduling of collection times (Faccio, Persona & Zanin 2011) are addressed in regards to socio-ecological impacts. A special topic in this context focuses on locating disposal plants for hazardous waste (Nolz, Absi & Feillet 2014), for example, infectious medical syringe, to reduce public health risks. Figure 2.3 illustrates the various research scopes found in CSC.

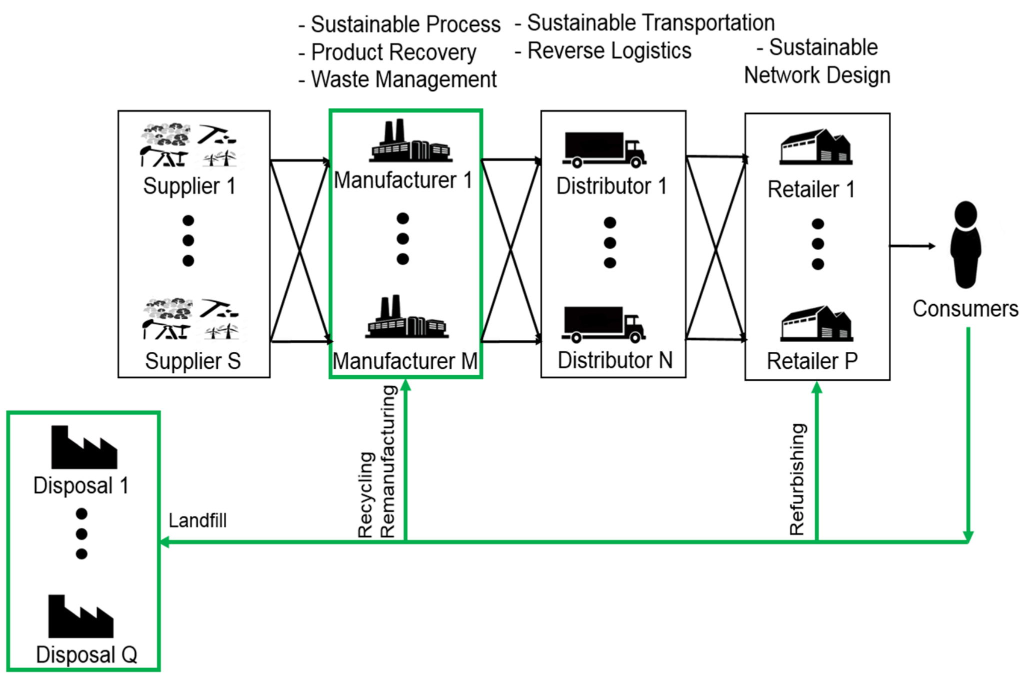

Figure 2.3. Research conducted in the circular supply chain area

2.2.4. Sustainable circular supply chain

Reducing waste and need for virgin raw materials are the provided justifications for this assumption that CSC is inherently sustainable (Melachrinoudis 2011; Srivastava 2008). The validity of this claim is under question unless CSC supported not only the reverse logistics activities but also the design of green products. Accordingly, the next generation of CSC, sustainable CSC, achieves the best socio-environmental values in alignment with the value circle, from value proposition (i.e., designing green products), to value delivery and creation (i.e., incentivizing for going circular), and value capture (i.e., Reduced environmental burden) (Geissdoerfer et al. 2018).

Value proposition focuses on offering sustainable products and services to ensure profit and minimize socio-environmental impacts while value creation is handled via incentivizing actors to collect and return disposal (Accorsi et al. 2015; Mota et al. 2018).

Sustainable/green **product design** is now seen as the leading strategy for saving resources and reducing adverse eco-effects (Leigh & Li 2015). Various potential designs of a product along with different configurations of supply chains should be analyzed to come up with the optimal product design. Generally, product design strategies can be categorized into two streams:

(i) Designing products with the application of cleaner production principles to decrease environmental impacts and resource dependency, known as design for material efficiency and sustainable production (Stindt 2017).

(ii) Designing products that have longer life cycle and can be easily taken apart at the end of life so that these parts can be reused, called design for sustainable usage and design for recovery (Stindt 2017).

In the former strategy, the harmful or resource dependent components of a product are identified and replaced with eco-friendly materials (Hassini, Surti & Searcy 2012). This strategy requires significant investments as new cooperation with green material suppliers may need to be established and new technologies for processing these materials and producing environmentally friendly products need to be implemented. The new design is to reduce toxic use, waste and necessity for post-use treatment. The latter strategy, however, tries to preserve the inherent value of products for as long as feasible. The objectives of this strategy are compatible with the preventive design strategy but the focus shifts to enhanced durability, product–service combinations, updatability via software upgrades, or manufacturability approaches (Munasinghe et al. 2016). Here, the products are designed for remanufacturing, disassembly or recycling. Such products can be easily, cost-effectively and rapidly dismantled in their post-use phase so that parts can be either reused or recycled (Bansal 2005). The waste management policies and availability of appropriate technologies can explicitly influence the success of this strategy. For instance, governmental regulations, such as a fee on disposal and waste take-back, in which manufacturers are responsible for collecting and treating their end of life products, motivates the adoption of design for disassembly strategy (Tang & Zhou 2012). Similarly, investment should be made in technologies that increase the re-manufacturability of returned products. Technology selection decisions should be taken not purely in accordance with the economic and technical factors (e.g., production costs, process flexibility), but also with socio-environmental factors (e.g., rate of waste generation, energy consumption, safety index, etc.) (Tang & Zhou 2012). Examining the sustainability impacts of adopted technologies is an important lever for supply chains involving sustainability improvements (Tang & Zhou 2012).

Addressing the socio-environmental impacts of products has become one of the main design challenges in the last two decades. Thus, in the first step of green design, the footprints of a given product are analyzed across its entire life cycle, from the point of origin to the point of production-consumption and post-consumption. This provides designers with important information regarding the potential hotspots for resource savings or pollution reduction in the production cycle (Munasinghe et al. 2016). According to the identified hotspots, supply chain decisions are made with respect to the design strategies and possible improvements in the operations. **Life cycle assessment methodologies** such as life cycle assessment (LCA) and social life cycle assessment (sLCA) are appreciated as tools for quantifying the sustainability impacts of various products, processes and industrial systems for both research and practical needs (De Luca et al. 2017). It is noted by many scholars that green product design is linked to the product LCA results. These results highlight the most impactful areas of a product life cycle and help researchers to determine potential improvement scenarios to reduce impacts (De Luca et al. 2017).

LCA evaluates the environmental impact of a given product, from raw materials extraction through to production and recycling/incineration along its life. There is a growing consensus on the use of LCA approach in SSC studies as an objective methodology for appraising different typologies of environmental impact Since the LCA approach offers a broader environmental impact analysis throughout the product life cycle and allows for comparisons of various products, it fits well within the discourse on sustainability (De Luca et al. 2017). In addition, sLCA aims at quantifying the social impacts derived from many different factors during each life cycle phase of a product.

Despite the usefulness and popularity of the LCA approach, its full implementation hugely depends upon the nature of given products and the standardization level of the production process (De Luca et al. 2017). Although LCA evaluations have already been conducted for a wide range of products, in some cases we run into methodological challenges. These challenges are related to defining the functional unit, collecting data or analyzing the inventory. For food and agricultural products, as an example, data collection under various farming systems (organic or non-organic), climatic factors and local environmental elements (e.g., soil type, water availability) requires much effort (De Luca et al. 2017).

In case of sLCA, there is no consensus among researchers regarding the social impacts assessment. On the one hand, due to lack of methodological standardization, there is neither an agreed structure nor a unique evaluation process for the sLCA approach (De Luca et al. 2017). On the other hand, a clear definition of social responsibility has not been proposed mainly because it has a multi-disciplinary and multi-stakeholder nature (Chaabane, Ramudhin & Paquet 2012). Therefore, the incorporation of sLCA into SSC studies faces many challenges and its full implementation is still not practically possible (Popovic et al. 2018).

For these reasons, in many papers on sustainable CSC, researchers are likely to use partial LCA methodologies. Depending on the characteristics of the products that are to be investigated, this method focuses only on the most impactful environmental impacts categories or covers particular life cycle stages (e.g., cradle to gate versus cradle to cradle to undertake the assessment (Eskandarpour et al. 2015). Acidification, eutrophication, global warming, ozone depletion, photochemical ozone creation, and energy use are the big six impact categories of LCA.

Despite the popularity of partial assessments, a number of researchers questioned the validity of its results. Schlegel et al. (2016) criticized the results of partial assessment of road construction practices by comparing them to the results of more comprehensive assessments. Valuable sustainability outcomes can be lost and wrong environmental decisions may be made, if a predefined, limited set of environmental or social indicators are used for impact assessment (Michelsen, Fet & Dahlsrud 2006). To address this concern, participatory life cycle sustainability assessment (LCSA) framework was developed recently to partially assess the impacts that are most important for particular groups of stakeholders. LCSA is an aggregation of LCA, sLCA and life cycle costing methodologies devoted to comprehensive sustainability evaluation. Participatory approaches in this framework refer to those techniques and methods (e.g., multi-criteria decision making, multi-attribute utility theory, etc.) that allow the involvement of stakeholders, particularly those who are affected by the impacts of products and processes (Ekvall et al. 2016; Guijt 2014). The involvement of participatory approaches in LCSA enables stakeholders to decide on assessment scope, indicators, weights and aggregation methods (De Luca et al. 2017). The practical use of comprehensive approaches for measuring the effectiveness of supply chain like participatory life cycle sustainability assessment is to be considered more in future research. Figure 2.4 summarizes the issues that are described in the text above.

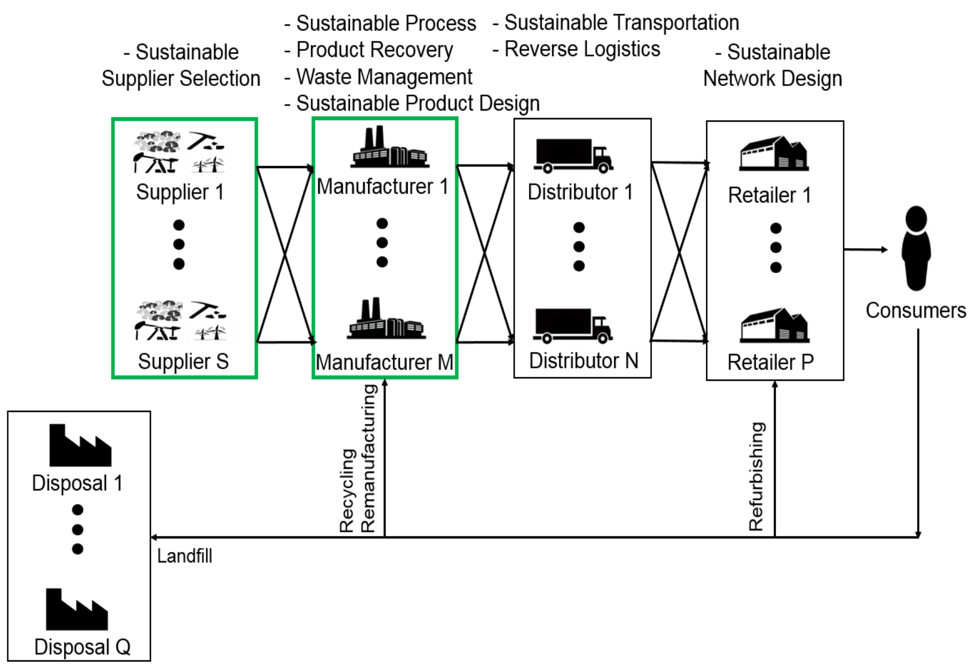

Figure 2.4. Scope of sustainable circular supply chains

2.3. Towards the ESSC conceptual framework

2.3.1. Sustainability and financial performance

The relationship between the efforts towards making SC sustainable (including SSC, CSC and sustainable CSC) and their financial performance has been investigated in a large body of literature (see review by de Oliveira et al. (2018)). The results are contradictory: some studies found efforts towards sustainability in supply chains as financial burdens, whereas, others reported increased profitability and competitiveness (Wu & Pagell 2011).

Environmental efforts such as minimization of resource consumption and reducing the fossil fuel consumption do reduce the costs and increase profits but may require upfront investments. The implementation of green technology, designing green products, and going circular are not quite aligned with cost-saving objectives. The investments in new design and technologies may take a long time to get paid off. Longer returns on technology investment put the financial health of the supply chain at risk (Mathiyazhagan et al. 2013). Munasinghe et al. (2016) found that adjusting an already existing supply chain to produce new low carbon products was more costly and difficult compared to designing the appropriate production processes from scratch. Xia, Govindan & Zhu (2015) report that in most small and medium size supply chains, funding for research on design for disassembly or remanufacturing is often cut and reverse logistics activities are limited to waste management. Also, other expenses related to green upgrades, such as energy efficient machinery and green materials tend to increase the total cost of products and ultimately the product prices (Eccles, Ioannou & Serafeim 2014). Therefore, for many supply chains that took steps towards sustainable development, costs have become a big concern (Bhanot, Rao & Deshmukh 2017).

Substantial upfront costs required for initiating a green revolution affect the financial strength and pure profit margins of supply chains adversely, at least in short term. The reduced financial performance and eroded competitive advantages causes uncertainties in stakeholders' decisions for going green, as the promise of improved benefits does not come true immediately (Nidumolu, Prahalad & Rangaswami 2009). Therefore, the major challenge facing supply chains is how to compensate for the increasing costs of transition towards sustainable SSC.

Despite the warnings by Pagell & Shevchenko (2014), most of the papers are still talking about financial gains and losses only in monetary terms. We argue that by incorporating societal preferences and norms into the SSC analysis, we have a better chance to account for other drivers that may not immediately translate into purely financial measurements. Decisions, like closing the resource loop or greening different processes, create a green image of the supply chain (Park, Sarkis & Wu 2010). The positive relationship between green image and environmental performance (Rao & Holt 2005) lead to enhanced competitive advantage, sales and market share, profit margins and superior economic performance (Schrettle et al. 2014). This immediately calls for deeper considerations of consumer behavior and how it can impact the overall success of the SC. People will be buying certain goods not only because they deliver more functionality for a lower price, but because they approve how they were produced and delivered, because they appreciate the SSC, no matter what the monetary costs are. Researchers highlighted that sustainable SSCs can both minimize socio-environmental impacts and maximize financial benefits (Zhu & Sarkis 2004). However, it is difficult to come to a clear conclusion because of changing market rules, varying regimes of taxation and subsidies. These in turn depend on governmental policies and decisions (Li, Chen, et al. 2018), further raising the importance of accounting for the consumer preferences and choices at the ballot boxes. Unless the social processes and dynamics are part of the analysis, we will not be able to account for all the delicate feedback effects and non-monetary metrics.

2.3.2. Sustainability and consumer behavior

Excessive use of natural resources to provide for ever-increasing irresponsible consumption of products and services in recent decades have prompted environmental degradation worldwide (Chen & Chai 2010). Consumption patterns and consumer preferences have a significant impact on environmental deterioration (Biswas & Roy 2015), and attracted attention of several researchers who study green consumer behavior. A set of terms such as green, eco-conscious, sustainable, responsible, and pro-environmental behavior have been used to define consumers' care for the environment (Kumar & Polonsky 2017). However, consumer behavior has been receiving little attention in the context of supply chains. The few examples that we found include Pankaew & Tobe (2010), who studied whether the greenness was a selection criterion for electronic device consumers, and Dan-li, Zhen & Hong-yan (2011), who demonstrated that the demand of consumers could be shifted towards green products by adopting competitive price strategies. Coskun et al. (2016) proposed a model for the green supply chain network design based on consumers' green expectations.

Making changes in diet, taking energy conservation measures, and managing and recycling waste are a few examples of desirable pro-environmental behavior change. Some people choose to ignore the environmental impacts of their purchases and explain the negative environmental messages about products to marketing attempts. They undermine the green products value and question whether a green product is worth the higher price. Changing the irresponsible behavior of this group is hard, just like changing any other human behavior.

A wide-range of complex factors influence environmentally responsible purchasing and eco-conscious behavior. These factors can be generally classified as individual factors and situational factors (Joshi & Rahman 2015). Individual factors related to green behavior are derived from the individual's personal traits, cultural norms, education, subjective knowledge, and life experiences. Individual factors including environmental concerns and responsibility, perceived consumer effectiveness, perceived behavioral control, values and personal norms, and knowledge positively influence green consumption behavior (Groening, Sarkis & Zhu 2018). However, environmentally damaging habits and lack of trust in green products can deter individual actions toward ecologically-conscious consumption behavior. Situational factors are concerned with the circumstances and situations in which a person makes decisions (Joshi & Rahman 2015). Situational factors such as product price, availability of products and alternatives, social norms and reference groups, product quality, store related attributes (e.g., size, location, etc.), brand image, eco-labeling, and certifications can impact pro-environmental consumer behavior (Joshi & Rahman 2015). All these individual and situational factors can discourage or encourage green purchase behavior, but the extent to which they influence sustainable behavior requires further research.

While the rate of environmental degradation is rapidly increasing, the changes of individual behavior to more sustainable purchasing practices are much slower (Taufique & Vaithianathan 2018). Thus, after identifying the causal factors of a particular green behavior, it is necessary to adopt intervention strategies that target the promotion of relevant behavioral factors. A set of various strategies for different behavior determinants have been proposed to promote green changes. They are broadly classified into informational and structural strategies. The former are aimed at changing the individual factors of green behavior (e.g., green concern, knowledge, personal norms), whereas, the latter focus on the situational factors influencing environmental behavior (e.g., price, availability, social norms) (Abrahamse et al. 2005). Prompts and information campaigns, individualized social marketing, social support and role models, public involvement and participatory approaches are examples of effective informational strategies for the adoption of pro-environmental behavior (Steg & Vlek 2009). Structural strategies are associated with, for instance, providing better behavioral options, making environmentally harmful behavior less feasible or infeasible, rewarding good and punishing bad behavior, and proposing financial and legal measures (Steg & Vlek 2009). The effectiveness of these strategies in orienting people's behavior towards greenness depends on the characteristics, motivation, regional culture, and situation of different target groups.

Consumer behavior shows not only in the purchasing decisions that are made, but also impacts the governmental performance and the policies that are delivered. These in turn feed back into human behavior. The impact of government policies on pricing of eco-friendly products (Li, Chen, et al. 2018) and waste management (Zand, Yaghoubi & Sadjadi 2019) has been well documented and only confirms importance of close integration of social, behavioral aspects into the SSC analyses.

What is most important, and what we see from the overall effectiveness of various commercials and advertisement methods, is that changing consumer preferences and behavior is possible, and it would be inappropriate to ignore or overlook it when designing and managing supply chains in a sustainable way.

2.3.3. Extending circular supply chain for sustainability

Much of the supply chain success depends on the extent to which it is capable of predicting and meeting customer expectations. One of the principles of supply chain management is that customer demand drives the entire supply chain, pulling products through production and distribution processes. The demand-driven supply chain or customer-centric supply chain terms resulted from customer-focused thinking approach. Likewise, in today's green economy, environmental needs of consumers have profoundly influenced the disposition of supply chains for transition towards SSC. In fact, the pro-environmental behavior of supply chains is guided by customers' attitude towards eco-friendly products. That is to say, the consideration of green consumer behavior in the management of involved companies on the supply chain is critical (Lacoste 2016).

Paying attention to consumer demand and preferences is crucial for addressing sustainability. We cannot claim that a supply chain is sustainable unless we consider both the impacts on natural resources and the society. Consumer preferences are key to making sure that supply chains are modified to take into account sustainability issues. Without additional support and incentives from consumers, it is unlikely that SSC can be competitive and financially viable. Consumer choices and their willingness to pay more for green products can make sustainable products more competitive. The focus on sustainability in SC can, in turn, influence consumer behavior and raise their awareness about socio-environmental concerns. We, therefore, propose a conceptual framework (see Figure 2.5) to emphasize the importance of consumers and their green behavior for sustainability features of supply chains.

The "Extended Sustainable Supply Chain" (ESSC) can be considered as an extension to the traditional concept of sustainable circular supply chain that includes behavioral aspects of consumers. ESSC is motivating sustainable consumer behavior to drive decision-making process along the whole SC for improving socio-environmental performance. By extending the supply chain analyses to include consumer behavior we may be entirely changing the goals/objectives used in the supply chain optimization efforts, and, therefore, affecting the performance of the supply chains. If consumers are motivated to switch from purely economic cost/benefit considerations when making their purchase decisions, and start to bring in additional considerations about environment, social and intergenerational justice, ecological and human health, etc., then these preferences start to feed back into the design and organization of the supply chain. As a result, we will likely see very different solutions and investment strategies becoming dominant.

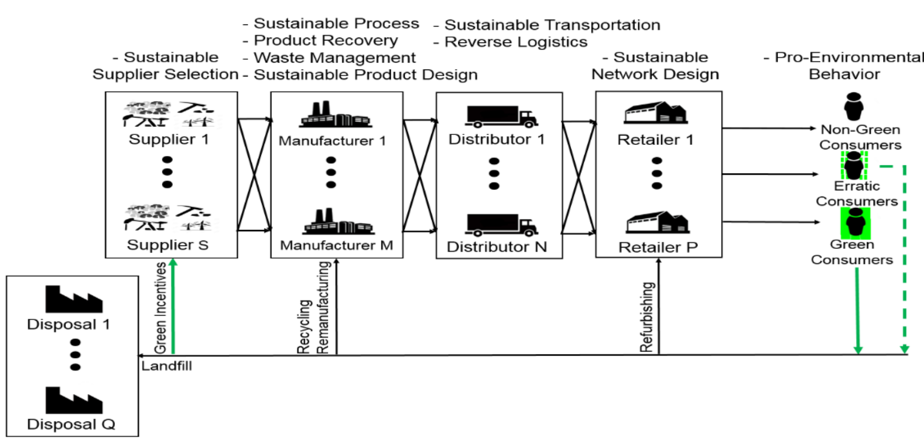

Figure 2.5. Extending circular supply chain to address sustainability (ESSC framework); where _____ represents the feedback from green consumers and - - - represents the feedback from erratic/uncertain consumers

As discussed above (see section 2.2), SSC literature had no (as in traditional SSC) or poorly defined relationships (as in CSC and sustainable CSC) between upstream firms and final consumers, making it difficult for suppliers (i.e., manufacturer, distributor, etc.) to perceive and influence green consumer expectations (Lacoste 2016). Also, the results of literature analyses show that green consumer expectations have been either left out of consideration entirely or just touched upon (Govindan 2018; Tseng & Hung 2013).

Current SSC studies assume that consumers make entirely informed choices based on rationality. So far, rational behavior optimization and immediate equilibrating process in markets are used for demand modelling which is very different from the way consumers actually behave. The growing literature in social science emphasizes that many issues in consumer pro-environmental behavior are complex (Bamberg, Rees & Seebauer 2015); that the choices the consumers make are influenced by behavioral factors (e.g., attitudes, norms) rather than the more predictable rationality. Underestimating these factors, analyses of market changes can be misleading. This is especially important in the context of sustainability, which is a largely social concept and assumes that consumers can substantially change their preferences, values, and behavior. Consumers can be influenced by information (awareness campaigns, targeted advertisement), they can learn from the behavior of other consumers (neighborhood effects). These changes, in turn can significantly modify demand and drive the whole SC. These aspects are largely ignored in existing research on SC.

In the ESSC framework, the customer behavior is considered through identifying different market segments and influencing their green purchasing behavior. The results of market segmentation in regards to sustainability shows three general categories of green, erratic, and non-green consumers. Green consumers pay significant attention to socio-environmental, as well as health impacts of products during use and post-use. Erratic consumers have some level of environmental awareness and intention, which might or might not lead to a green behavior. Non-green consumers, buy products with no concern for their environmental or social impacts, making their choices based only on their selfish cost/benefit considerations, or simply lacking information and awareness about the sustainability issues. These statements stand true only when consumers do not struggle to survive and their living condition do not force them to prioritize needs.

The sustainability efforts of suppliers, manufacturers, distributors and retailers should be adjusted to meet the expectations of each segment. Not only meeting each particular demand is the ultimate objective, but ESSC aims to see how this demand is formed and how it can be modified to increase the market share of green consumers and decrease the negative socio-environmental impacts. Factors affecting green consumers purchasing behavior and intervention strategies were discussed above in Section 3.2. With this setting, supply chains can reduce the resistance of partner organizations to change their unsustainable approaches and initiate their transformation efforts towards sustainable development. Just like advertisement is largely responsible for creating the current consumer society, similar efforts, but probably in the opposite direction, are required and should be expected if we are to move toward sustainability.

As we discussed in Section 2.3.1, many supply chains that begin their journey towards sustainability are hesitant about making changes because of concerns about their profitability after the transition. Green materials, for instance, tend to be more expensive (Wu & Pagell 2011). Replacing hazardous materials with them would raise the overall cost of production and prices of final products (Beske, Koplin & Seuring 2008). However, if consumers are willing to pay more for the green products, the extra cost will be transferred to them and compensated for the producers. At the same time, we should be prepared that while paying higher per unit prices, consumers may be inclined to decrease the overall number of units to be purchased, which will certainly impact the overall performance of the SC.

Consider the following cases in food and garment production. In a food supply chain, if consumers are persuaded that organic, ethical food (i.e., fair trade (O'Connor, Sims & White 2017)) are better for health, environment, society, and thus worth the extra cost, they will be then willing to pay a higher price for such products (Rödiger & Hamm 2015). By doing so they provide financial support for mitigating the risks involved in organic food supply chain. These risks are not only limited to real physical risk (e.g., threat of pests destroying crops) but also they are related to the costly process of getting certified (at least 750 USD in the United States) and timely conversion from conventional to organic farm (approximately 3 years). According to the International Federation of Organic Agriculture Movements (IFOAM) and Food and Drug Administration (FDA) regulations, organic food producers are responsible for meeting sustainability requirements in all supply chain stages, from farm management and transportation, to storage and packaging (Marques Vieira et al. 2013). Because of the high risk of organic food contamination, it cannot be carried with other food in trucks and cannot be stored together with conventional food. This may lead to an increase in complexity of logistics and supply chain management as additional provisions are required for organic product transport. Garment industry is another example showing how changing consumer behavior can address environmental issues of supply chains. Raw material production is reported to be the most environmentally impactful phase of garment life cycle (Bevilacqua et al. 2011). However, research showed that garment usage phase which is dependent upon the customer behavior could be even more harmful. In particular, for sensitive fabrics, washing followed by drying and ironing was the most energy-intensive activity (Dewaele et al. 2006). Changing washing habits can reduce carbon emissions by 2% and energy by 4% per product (Munasinghe et al. 2016). The eco-friendly behavior of consumers can be extended to promote recycling. Textiles are then recovered and reused so that the dependency on virgin materials (i.e., cotton) is reduced and environmental performance is improved. Using cold-water detergent and washing machines at lower temperature settings provide another significant opportunity to reduce environmental impacts. The result of an LCA study on lowering washing temperature from 32 °C to 15 °C has shown a 300g reduction in CO2 equivalent per load as less energy was consumed to heat water (Nielsen 2005). Although using cold water can save money ($US 60 - 200 per year) and energy (GHG equivalent to 1000 miles of driving), some consumers do not perceive washing at cold temperatures hygienic (Mars 2016). Thus, increasing consumer awareness about the effectiveness and safety of cold-water washing is necessary to address their concerns and promote energy-saving habits.

These examples show how by raising consumer awareness and motivating behavioral shifts, the impacts of supply chains on environment are reduced. When turning conventional supply chains into sustainable supply chains behavioral changes may deliver as much economic and environmental efficiency as all the other technological/methodological developments in the field. Because of the multitude of feedback effects between the operation of the supply chain and the consumer behavior, we suggest that the two are integrated and considered jointly within the framework of ESSC, rather than bringing in considerations about consumers at the end assuming them to be beyond the SC analyses.

2.3.4. Application of ESSC in practice

In this section, we apply our proposed conceptual framework in two case study settings, forward SSC and sustainable closed loop SC. For each case, we explain how economic and socio-ecological performance can be improved if the companies revisit their practices in accordance to ESSC framework.

2.3.4.1. Extending a SSC for bicycles

Park, Kremer & Ma (2018) proposed a SSC model focusing on sustainable supplier selection and optimal order allocation. They aimed to minimize total cost, defects, delivery delays and carbon footprint of global supply chains. In this study, initially, a set of supplier regions (countries) were determined based on regional sustainability indices and then the final suppliers were selected from the list of candidate regions. The performance of the model was demonstrated in a bicycle SC case study with a budget of $9 million to meet a demand of 12,000 units. Their analysis indicated that the optimal solution reached 75.6% or 77.3% of the ideal solution if the decision maker gave higher values to cost or environmental impact objectives, respectively. Although environmental impact-oriented strategy had the best carbon reduction performance (dropped from 2,130,176.63 kg CO_2 equivalent to 1,849,144.51 kg CO_2 equivalent), the total SC cost was significantly higher (growing from $7,234,691.92 to $5,999,539.12). They concluded that the consideration of sustainability in SSC can be challenging.

We suggest using ESSC framework to address this challenge through applying behavior change to increase the number of people cycling, which eventually will increase the demand for bicycles. Biking is one of the most sustainable means of transportation. The estimated climate impact of riding a bicycle is 40-65 (g CO_2/passenger/km) while driving a car has an impact of 300 (g CO_2/passenger/km) (Thorpe & Keith 2016). Using a bicycle for trips of up to 10 kilometers (each way) can save 1500 kg greenhouse gas emissions per year per individual (Queensland Government- Department of Transport and Main Roads 2018). Increasing education, awareness, effective communication and social support as well as reducing the perceived risks of cycling can motivate people to change their behavior and start riding on a regular basis. For example, management and regulations could be directed towards increasing the connectivity and safety of cycling routes and raising awareness about the benefits of cycling for the rider (e.g., healthy lifestyle, burning calories, saving transportation costs) and for the society (e.g., less road traffic, less need for fuels, more carrying capacity of public transport). As a result of such measures, the proportion of people in the City of Sydney, Australia, who have ridden their bicycle to work have doubled in a 10 year period (2006-2016) (NSW Government- The City of Sydney, 2018).

Such practices as organizing events (e.g., speed dating, charity rides), providing cycling courses and informational campaigns, or funding projects for improving the usability, accessibility, and attractiveness of biking can be considered as parts of the bicycle ESSC to develop a more profitable, environmentally-friendly and socially-favorable business.

2.3.4.2. Extending an SCSC for tire production

Sahebjamnia, Fathollahi-Fard & Hajiaghaei-Keshteli (2018) designed a SCSC model to address supplier selection and location-allocation problems for the tire industry. The sustainability objectives were defined as minimizing total network costs and total environmental impacts as well as maximizing social benefits. The market demand for different tire types and the fraction of used tires returned from market were assumed to be deterministic and unchanging. They numerically showed that if the amount of collected and recycled tires are increased, the total costs of economic considerations will decrease and the social impacts (due to availability of more job opportunities) will improve. In this study, no explanation was given to understand how the number of scrapped tires is to be increased, how consumers can be motivated to return their products back to the collection/distribution centers and what dynamics are involved in consumer behavior. The ESSC framework can address this gap by suggesting to use behavior change strategies to motivate waste recycling decisions of consumers. In Figure 2.6, we demonstrate how can Sahebjamnia, Fathollahi-Fard & Hajiaghaei-Keshteli (2018) CSC framework be extended.

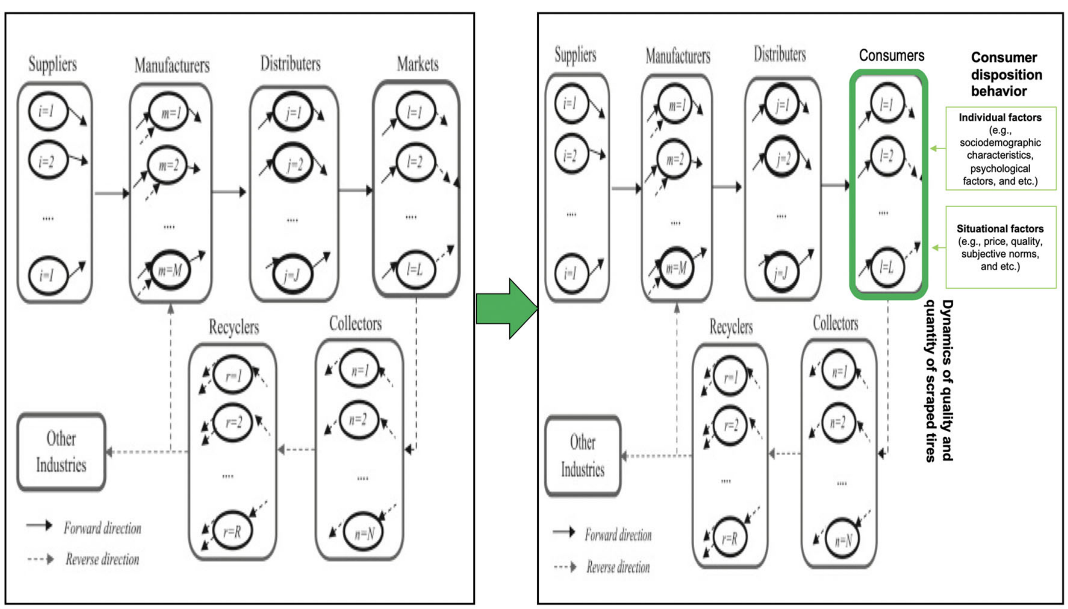

Figure 2.6. Comparison of tire closed-loop supply chain network developed by Sahebjamnia, Fathollahi-Fard & Hajiaghaei-Keshteli (2018) (left hand side) and proposed tire extended closed loop supply chain (right hand side). We suggest replacing markets agent with consumer's agent to investigate used tire disposal behavior of consumers

For designing appropriate change strategies, we first need to identify what individual and situational factors influence the disposition behavior. Gaur et al. (2016) categorized these factors as psychological, product-related, situational, and cultural. They highlighted that in many cases, lack of information about take-back policy of companies, absence of financial incentives, and poor access to collection centres are the main reasons discouraging consumers to return the used products. Considering both the individual and situational behavioral factors, the suggested framework gives a more realistic understanding of the product acquisition process for remanufacturing. The quality and quantity of returned tires can be increased if the company makes the return process easy by offering free shipping, locating collection centres close to consumers, providing financial/non-financial incentives for returns, informing consumers about the return policies, or creating a local culture for recycling through education and information campaigns. Effective product return strategies can result in higher profitability of the company, lower environmental impacts, and cheaper remanufactured products for the consumer.

2.4. Conclusions and outlook

In this paper, we suggest that an extension of the supply chain concept is needed if we want to analyze their sustainability. First, we present an overview of the evolution of the SC concept with respect to sustainability goals. To this end, we select some most relevant papers and critically compare and contrast them. Summarizing literature on sustainable supply chains, circular supply chains and sustainable circular supply chains, we show why they were not quite adequate to address the holistic and system wide sustainability issues. We discuss the sustainable forward logistics issues in SSC and the integration of circular economy concepts with the supply chain organization. The relationship between LCA methodologies and CSC is examined in the context of sustainable CSC. This review clearly demonstrates how the SC concept has been evolving to include additional processes and actors, to consider the requirements of sustainable development.

Next, we show how financial performance of supply chains may be influenced as a result of implementing green practices such as green technology, green product design, and end of life treatment. Most supply chain managers conclude that their competitiveness is eroded with increases in the cost of green products. Furthermore, we explain consumer choice behavior in purchasing green products and strategies to motivate pro-environmental behavior. By doing so, we set the foundation to consider the role of green product consumers in SSC.

To address sustainability in future research on SC we propose a conceptual framework which links three very different areas (i) supply chain design and engineering, (ii) financial performance, accounting and economic optimization and, (ii) consumer behavior and environmental psychology. Figure 2.7 shows the evolution of sustainable supply chain concept in literature and how we think it should further develop. Our findings demonstrate how financial performance of SSC can be improved by bringing the consumer into the picture and exploring how their willingness to pay and sustainability concerns can be influenced and modified. Although it is important for the focal firms to identify possible strategies for motivating pro-environmental behavior of stakeholders, particularly consumers, SSC studies are still far from providing comprehensive analytical studies. Disregarding the relations between SSC and consumer behavior leads to a blurred notion of sustainability in supply chain research. From a theoretical perspective, we argue that for transition towards sustainability, it is crucial to take the extended supply chain view, in which the boundaries are expanded towards the involvement of consumers and their behavior.

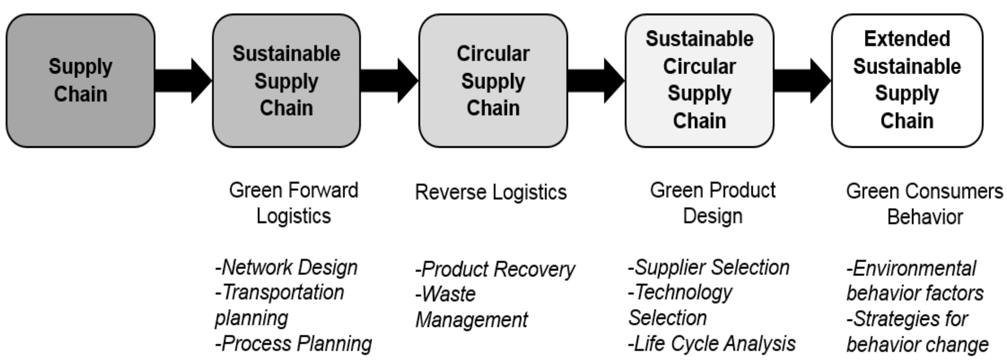

Figure 2.7. Comparison of scopes for conventional, green, sustainable and extended supply chains

We invite sustainable supply chain analyses to go beyond their tradition scope of operations, and bring consumer behavior dynamics into consideration. It is important to identify the factors influencing consumer choice behavior regarding sustainable products and apply appropriate interventions to change unsustainable consumer behavior. The growing field of behavioral and empirical economics and the proliferation of agent-based modeling methods, can now look at heterogeneous human behavior under various conditions, and can help understand and quantify some of the cultural and social drivers that affect SC (Anufriev, Hommes & Makarewicz 2018; Filatova et al. 2013). These models can be well integrated with SSC models to include the social dynamics in SC design and management (Taghikhah, Voinov & Shukla 2018). They can be used to improve SCM and offer additional control parameters for optimization of SC performance. The ESSC framework assumes that other managerial techniques should be also employed, with a focus on the social dimension, on education, motivation, nudging and persuasion as part of development towards sustainability.

We hope that the ESSC framework can help supply chains to become green and to gain competitive advantage and improve visibility of sustainable practices in the evolving marketplace. A future extension of this research will consist of developing analytical studies to compare the performance of extended sustainable supply chain with conventional frameworks. Another extension can be to empirically analyze the impact of adopting behavioral change strategies for green demand and green supply. Future studies can develop tools and models to deal with the difficulty of prediction and high uncertainties involved in behavioral aspects of green consumption.

2.5. Author contributions

Conceptualization: F.T., A.V. and N.S.; methodology: F.T., A.V. and N.S.; investigation: F.T.; writing—original draft preparation: F.T.; writing—review and editing, F.T., A.V. and N.S.; visualization: F.T.; supervision, A.V. and N.S.;

Chapter 3:

Exploring Consumer Behavior and Policy Options in Organic Food Adoption: Insights from the Australian Wine Sector

Firouzeh Taghikhah, Alexey Voinov, Nagesh Shukla, Tatiana Filatova

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Abstract

Organic food has important environmental and health benefits, decreasing the toxicity of agricultural production, improving soil quality, and overall resilience of farming. Increasing consumers' demand for organic food reinforces the rate of organic farming adoption and the level of farmers' risk acceptance. Despite the recorded 20% growth in organically managed farmland, its global land area is still far less than expected, only 1.4%. Increasing demand for organic food is an important pathway towards sustainable food systems. We explore this consumer-centric approach by developing a theoretically- and empirically-grounded agent-based model. Three behavioral theories – theory of planned behavior, alphabet theory, and goal-framing – describe individual food purchasing decisions in response to policies. We take wine sector as an example to calibrate and validate the model for the case study of Sydney, Australia. The discrepancy between consumer intention and purchasing behavior for organic wine can be explained by a locked-in vicious cycle. We assess the effectiveness of different policies such as wine taxation, and informational-education campaigns to influence consumer choices. The model shows that these interventions are non-additive: raising consumer awareness and increasing tax on less environmentally friendly wines simultaneously is more successful in promoting organic wine than the sum of the two policies introduced separately. The phenomenon of undercover altruism amplifies the preference for organic wine, and the tipping point occurs at around 35% diffusion rate in the population. This research suggests policy implications to help decision-makers in the food sector make informed decisions about organic markets.

3.1. Introduction

Food production-consumption is one of the most energy and resource-intensive activities of modern civilization. It accounts for 15-20% of the total global anthropogenic greenhouse gas (GHG) emissions (Woods et al., 2010) and has a significant environmental impact. Expanding conversion of natural habitat to agricultural land is the main driver of global forest loss and species extinction. Since the introduction of chemical fertilizers in the 19th century, food production has significantly contributed to a wide range of environmental problems. Organic agriculture as part of the solution can largely reduce the overall environmental footprint of food production by eliminating the application of chemical fertilizers and pesticides and reducing energy use (Pizzigallo et al., 2008). According to the 2019 IPCC report (IPCC, 2019), by changing diets, and in particular, by transitioning to organic food production and consumption we can reverse environmental losses and avoid ecosystem collapse. There are examples of quite successful and productive organic farmlands, where species diversity and soil quality are substantially higher than in conventional systems (Wilbois & Schmidt, 2019). Organic food also contains higher levels of nutrients, improves consumers' health and wellness. Organic diets have been convincingly exposing consumers to fewer chemicals associated with human diseases such as cancer, autism, and infertility (Hyland et al., 2019).

While organic farming is more sustainable, it usually produces lower crop yields in comparison to conventional agriculture, resulting in higher food prices. Consumer food preferences and higher interest in organic food can be a turning point in motivating farmers to adopt organic farming practices (Wheeler, 2008). Therefore, by purchasing organic food, people not only improve their health and well-being but also subsidize eco-friendly agriculture.

In 2018, the global sales of organic food reached US$ 89.7 billion, a 10% increase from the previous year. The United States has the biggest organic market by value (Mosier & Thilmany, 2016). Germany, France, Italy, and Spain also started their organic consumption-production movement turning Europe into the second-largest organic food market. Still, the average share of organic food spending remains low (Lawson et al., 2018). Despite the efforts in promoting organic farming, according to the International Federation of Agriculture Movements, only 1.4% of global farmland was organic in 2019.

There are a number of reasons for the lower interest in organic food. According to a recent Australian organic market report (2018), higher prices, lack of trust, and lack of knowledge are identified as the top three barriers for organic purchases. In general, Australians do not value organic products much more than conventional ones, are not willing to pay more for sustainability features, and are much less willing to pay premium prices for organic food (Lockshin & Corsi, 2012). As a result, farmers lack the motivation to continue their organic farming.

A specific sector of the food market consists of so-called vice products. Vices and virtues are typically defined relative to one another. Vice foods or “wants” refer to products that are more gratifying and appealing in the short term but have negative health impacts in the long-term such as chocolate, chips, wine. On the contrary, virtue food or “shoulds” may not possess the hedonic allure of vices or immediate pleasurable experience but provide utilitarian benefits. Generally, consumers are highly motivated to consume more vice food rather than virtue food. Research indicates that organic labels of vice and virtue food types may cause different responses among consumers (Muñoz-Vilches et al., 2019). On the one hand, Van Doorn and Verhoef (2011) report that consumers pay more price premiums for organic virtue food in comparison to vices due to negative quality connotations for vice products.

On the other hand, Lee et al. (2018) show mixed results, where the organic label on vice food both increases and decreases food intake depending on consumer characteristics. They declare that consumers’ perception of external and internal health control is the mediating factor in decisions between organic and conventional alternatives. A consumer who believes in external control is more likely to buy organic vice food because that provokes a guilt-reduction mechanism. A consumer being driven by internal health control may choose to do the opposite. The choice of organic in vice and virtue products is still an on-going topic calling researchers for further studies (Hidalgo-Baz, Martos-Partal & González-Benito 2017).

Empirical research on organic food preferences, so far, could not provide a clear understanding of the extent of interventions that can influence the behavior of consumers (Tait et al., 2019). In many cases, running an experiment requires much time (Bernabéu et al., 2013), and efforts before reaching the desired results, if reaching them at all. These limitations emphasize the need for methods that complement the empirical information about the complex behavior of organic consumers. System models can improve our understanding of the complexity of food purchasing decisions. Models are useful for designing interventions, comparing policy options, testing theories, and scaling behavioral patterns observed in experimental and field data. While statistical approaches are strong in revealing patterns in data, modeling methods such as agent-based modeling (ABM) add value by exploring causal connections behind system-level phenomena and patterns. ABMs not only study macro-level patterns emerging from actions of heterogeneous agents and their interactions with each other but also show the downward causation where the behavior of individuals at the micro-level is influenced by collective actions (Jager & Ernst, 2017). This makes ABM a suitable method for studying the complexity of cumulative market effects of individual behavior changes, especially for food preferences, where emerging social norms add uncertainty about future consumption choices.

ABMs becomes a key research method to explore the dynamics and impact of behavioral changes in marketing, food, health, and environmental sciences. Hu et al. (2018) examine the impact of promotional and marketing activities on consumer preferences. Li et al. (2018) develop a model for assessing the impact of access and price on New York's fruit and vegetable consumption. Garcia et al. (2007) address validation issues for ABM in the field of marketing focusing on the wine industry. Recent environmental applications include studying behavior change in energy markets (Niamir et al., 2018), low-emission cars (Kangur et al., 2017), waste management (Rangoni & Jager, 2017) and climate change adaption (Erdlenbruch & Bonté, 2018). Yet, the evidence on the impact of behavior change interventions on consumer preferences for organic food is scarce.

We address this gap by developing a computational model to simulate the decision-making process and explore the key stimuli that lead people to make choices between organic and non-organic wines in the complex shopping environment. A spatial ABM – ORganic Vine (ORVin) – explores the cumulative market consequences of individual consumer choices affected by behavioral biases and social influence. To gain insights into the process of organic wine consumption, we consider the Theory of Planned Behavior (TPB) (Ajzen, 1985) along with the Alphabet Theory (Zepeda & Deal, 2009) and the Goal Framing Theory (Lindenbrg & Steg, 2013).[1] We apply the model to the case of the Sydney Metropolitan Area by incorporating the results of a published survey about the wine preferences of 2099 heterogeneous households. The innovative contribution of this paper is three-fold. Firstly, we develop an ABM to advance knowledge about the effectiveness of behavior change policy instruments on diets by explicitly considering consumer perceptions of and preferences for organic products. Within the scarce modeling literature on behavioral change towards sustainable food, this is the first

[1] Appendix 3.B extensively explains how we conceptually connect these theories to understand the decision-making process in the wine context.

simulation model proposed to understand bottom-up choices between organic and non-organic wine and the policies that can impact them. Secondly, we explicitly trace the effects of social interactions, drinking habits and desirability factors on wine consumption behavior. Regardless of its taste, wine is greatly associated with festivity, fraternity, social norm and rarely consumed alone. Previously, social norms have not been considered as a factor for wine consumption behavior, yet they strongly influence how consumers choose organic products. Thirdly, this model can help to understand how to persuade consumers to make healthier choices, when dealing with vice products such as wine. Since organic wine is hardly perceived to be of higher quality than conventional wine, it is considered as an exception to the subjective norm. Appendix 3.A provides a detailed introduction with more references.

3.2. Methods

3.2.1. Case study

There is growing public concern about the environmental consequences of wine production. These issues are mainly related to water scarcity (Castex, Tejeda & Beniston 2015), land-use change and greenhouse gas emissions (Fleming, Rickards & Dowd 2015). Yet, while 42% of Germans reported willingness to purchase organic wines, the organic wine market in Germany is relatively small around 3.5% (Schäufele & Hamm 2018). In Australia, the 5th leading country in wine production, organic wine occupies only 6.9% of the total organic market, although a 120% rise was reported in the organic grape production from 2011 to 2014 (O'Mahony & Lobo 2017). In comparison to the wide consumption of organic milk and dairy products (22.3%), meats (16.2%), fruits and vegetables (11.9%) together comprising 50% of the Australian organic market, organic wine consumption did not grow significantly (Mascitelli et al. 2014). Although the wine industry has already engaged in climate change adaption, the adaptive purchasing behavior of wine consumers is yet to be investigated.

Organic wines have a higher content of antioxidants (30% more) and taste better than conventional wines. They often contain less preservatives, such as sulphur dioxide that is used for inhibiting unwanted yeasts and bacteria, and is the main cause of headaches and hangovers (Amato et al. 2017). Unfortunately, public awareness about health and environmental benefits of organic wines is rather limited as many people assume that all wines are produced in natural, organic ways.

Prior studies have reported that most grocery and supermarket shopping behaviors are unplanned (Forbes 2014). Hence, consumers have the temptation to purchase products without planning in advance. However, research on wine purchase behavior in a number of developed countries confirms that wine is an exceptional product. Particularly, in Australia, a relatively high level of planned purchasing behavior is reported. When purchasing wine, consumers look for attributes such as the country and region of origin, grape variety, price, and brand (Panzone 2014). In addition to these traditional wine attributes, sustainability labels and cues add to the complexity of consumer choices. While the bulk of literature on wine consumers focuses on studying purchase behaviors, there is not much research on drivers related to sustainability.

A review of literature on organic wine markets shows that a set of factors are involved in the choice of organic wines (Di Vita, Chinnici & D'Amico 2014). Among these factors, we find socio-demographics (D'amico et al. 2014), information seeking, knowledge, and beliefs (Loose & Lockshin 2013), wine characteristics (Panzone 2014), habit (Pomarici & Vecchio 2014), and social and personal norms. Regarding consumer characteristics, millennials, females and frequent wine consumers are more likely to choose organic wine. Moreover, consumers' environmental consciousness and health beliefs, which predict their attitudes, are also positively correlated with organic wine purchasing behavior. Specific extrinsic attributes of the product such as lower prices, higher quality, and organic labels, can all determine a greater consumer willingness for purchasing organic wines. Consumers who more frequently purchase wine reported higher interest in wines with sustainability attributes (D'amico et al. 2014); however, being stuck in a conventional wine shopping routine (habits) can lead to reverse outcomes. Although social desirability is an important issue for purchasing wine, especially organic, its influence on the wine purchase decision is yet to be addressed. As wine is largely a social product, subjective influence can have a direct impact on the acceptance or rejection of organic wine (Barber, 2012). Recently, Boncinelli et al. (2019) found that consumer wine choices are occasion-specific. They confirmed that people give greater value to organic certification attributes when purchasing red wine for gift-giving occasions. In another study, Galati et al. (2019) identify convivial drinking occasions as the explanatory variable with the highest impact on willingness to pay more for organic wine. A comprehensive review of these factors can be found in Schäufele & Hamm (2017).

3.2.2. Computational agent-based model of consumer behavior

Based on theoretical and empirical micro-foundations, we develop the ORVin ABM to understand consumer purchasing behavior regarding organic wines. Here, we briefly explain the model structure and properties and provide the detailed documentation in Appendix 3.C.

The ORVin model simulates the behavior and interactions between two agent classes: households and wine retailers. In particular, it explores household preferences for organic wine for a sample of households in Sydney, Australia. The city of Sydney is approximately 26.15 square kilometers and is home to over 103,844 estimated households with an average size of 2.2 in 2016. The **wine retailer agents** base their decisions regarding the wine stock in a rational manner to meet the local demand. Retailer agents differ in location but sale the same types of wine bundles. Organic and conventional wine prices are based on data provided by the Australian Government via 'Wine Australia [2]': at least AU$10.00 and 13.00 per bottle, respectively (taxes included).

A **consumer agent** – one household member purchasing weekly groceries of the family – is modeled in a cognitively rich manner. Hence, consumer agents are heterogeneous not only in socio-economic attributes, geographic coordinates of residence and wine shopping routines but also in their ability to learn, habits, perceived behavior control (PBC) and social norms. To gain insights into the process of organic wine consumption, we consider the Theory of Planned Behavior (TPB) (Ajzen, 1985) along with the Alphabet Theory (Zepeda & Deal, 2009) and the Goal Framing Theory (Lindenbrg & Steg, 2013). TPB is the most utilized theoretical framework to study organic food purchasing intention (Guido et al., 2010). The other two theories examine the role of psychological (e.g., habitual purchasing) and functional (e.g., contextual-environmental cues) factors on organic food consumption. This provides a solid theoretical framework for identifying cognitive and product-related factors (beliefs, attitudes, norms, habits, and goals) that may influence organic wine purchases. While prior literature attempted to explore the consumer intention for organic food, the barriers between organic food purchasing intention and behavior have been far less studied (Kushwah et al., 2019).

For consumer agent parametrization, we use the results of Ogbeide (2013a) who used a sample of 2099 responses (representative of the Australian population) to understand

[2] http://www.wineaustralia.com/

the factors affecting the willingness to pay for organic wine. Due to uncertainty in data, the initial conditions of several parameters such as the number of bottles per purchase, maximum expenditure on a bottle of wine, leaning capacity, etc. are determined as stochastic values (See Appendix 3.C.2).

Looking into the existing literature on organic wine purchasing, we could not find any study reporting data on **social network** characteristics. Nevertheless, when it comes to alcohol drinking behavior, social disorganization theory (Sampson 1993) highlights the importance of neighborhood environments (Shih et al. 2017). So, the social network of each household (macro-level network) includes neighbors living up to 400-800 meters away from them. The defined neighborhood type and buffer may influence the estimation of neighborhood effects (i.e., the effect of a particular neighborhood characteristic on wine choice) (Duncan et al. 2013). Individual relationships with peers and friends may modify neighborhood effects but are not included here due to the lack of data. Hence, ORVin focuses only on social interactions with neighbors where households exchange information about wine preferences and continuously update their perceived subjective norms about wine types. We also define another immediate social environment for each household: their observations of the wine choices of the surrounding consumers in shops (meso-level network). This social influence assumption is in line with the study of Scalco (2017) on consumer behavior for organic food. The number of social contacts that households may have is not predefined and is generated during the model run.

For this model, we define two sets of user-defined control variables: (1) tax rate (affecting wine prices) and (2) level of informational marketing activities (i.e., awareness and knowledge about organic wine). The production rate of organic and conventional wines and the delivery time of products are static. ORVin is programed in AnyLogic Software and the code is available online[3]. Most of households report shopping for wine at least once per week and thus the time step in the model is set to one week and run it for 600 weeks. Figure 3.1 schematically shows the weekly wine shopping journey of a consumer.

[3] https://www.comses.net/codebase-release/ef1972de-dff7-4d86-95e2-6509fa4443ba/

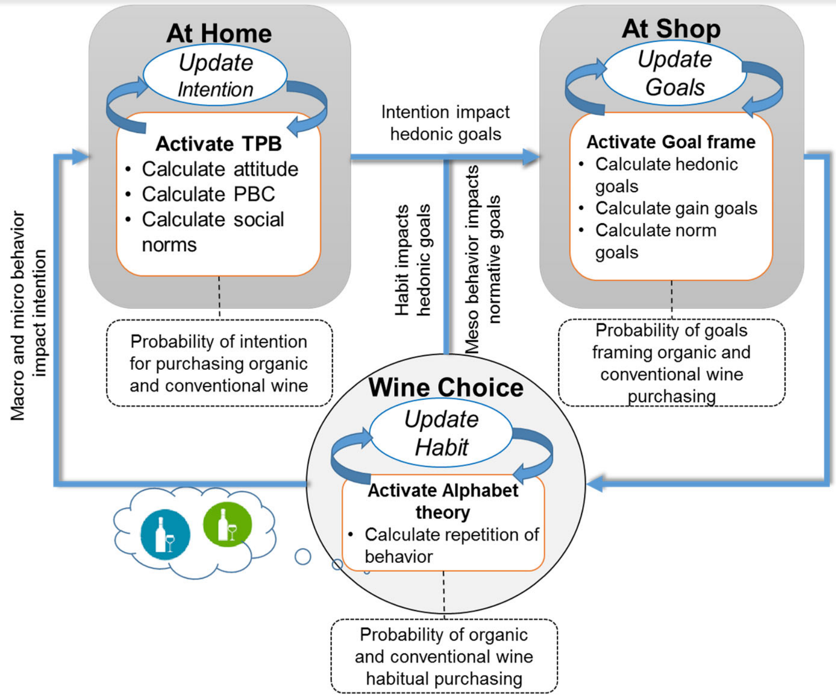

Figure 3.1. Household wine-related decision-making process

Following TPB, households make planned purchase decisions between organic and conventional wines, at home based on their attitude, price of wine at last shopping, and advice of neighbors. Every time they go shopping for wine, they consider the available wine retailers and visit the closest one. We assume that the retailers always meet the market demand, and no stock-out condition is allowed. The final choice is made at the shop according to the Goal Framing Theory. The Alphabet Theory is used to describe the effect of habit on purchasing behavior. These probabilistic theory-driven empirical rules of household behavior result in dynamic changes in wine preferences. Different control factors, such as wine prices and organic informational-educational campaigns, drive changes in consumers' behavior (See Appendix 3.C.3).

3.3. Results and discussion

3.3.1. Sensitivity analysis, calibration, and validation of results

We run an extensive sensitivity analysis. It indicates that the model is most sensitive to the weight of social norms and normative goals. The latter two parameters relate to a social phenomenon known as "undercover altruism" in organic purchasing behavior (Scalco, 2017). It assumes that individuals may choose to hide their virtuous, moral behavior in public to avoid awkward social situations, and integrate within a social group. Hence, in the absence of social pressure, people may be more likely to choose organic wines, bringing our attention to social norms and normative goals throughout the paper (See Appendix 3.D.1).

The values of parameters in the baseline setting are derived either from experimental data or by calibration using the One-Factor-At-a-Time (OFAT) method. We calibrate the model by adjusting the two most sensitive parameters to align the model results with available observed purchasing data. We made sure that the ratio of organic wine purchases stays constant at around 7-10% over 600 weeks (refer to Figure 3.2), as consistent with the trend of organic wine market share from 2014 to 2018 (See Appendix 3.D.2). Steady trends are also noticed for similar behaviors like the annual volume of wine consumption and per capita wine consumption (Statista 2017). Most probably, the strength of the effect of a social context on the wine purchasing behavior results in the locked-in consumption pattern, reported earlier (Janssen & Jager (1999).

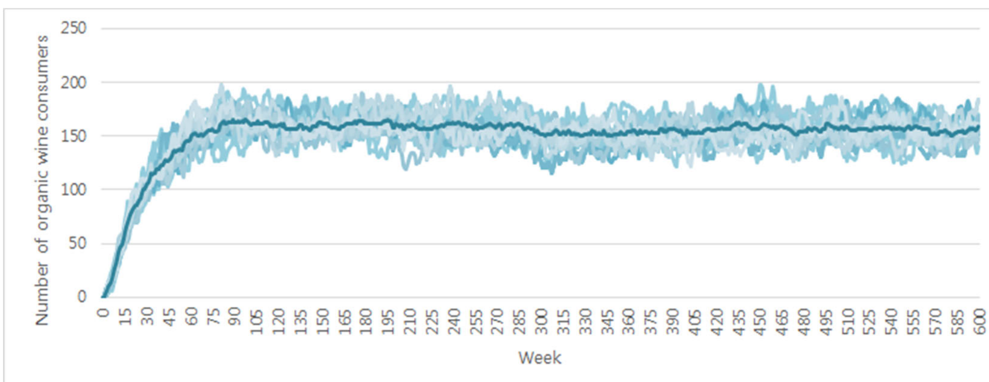

Figure 3.2. The result for the baseline scenario (20 runs) showing the variability in the model caused by stochastic parameters describing possible variations in human preferences and behavior

For validation purposes, we used empirical data reported by Ogbeide (2013a). We predict the intention of purchasing organic wine when the price of organic wines is 10%, 20% and 40% (and more) higher than conventional wines and then compare the estimated results with the available data in the baseline scenario. Appendix 3.D.3 reports the validation parameters and results.

3.3.2. Market-based instruments: restructuring the tax system

The objective of structural interventions is to increase the attractiveness of the desired behavior through changing the contextual factors shaping the decision-making process.

Three types of structural intervention include availability, financial and legal measures (Steg & Vlek 2009). For example, in terms of availability, the choice of an eco-harmful option can become less attractive when there are new eco-friendly alternatives. In our case, this strategy would limit the availability of conventional wines in stores and increase organic wine supply. This idea seems practically unrealistic in Australia since wine sales are decentralized.

Using financial measures would make the cost of positive pro-environmental behaviors cheaper than the cost of negative behaviors. Research on the consumption of alcohol confirms that selling alcoholic drinks at lower prices increases alcohol consumption and affects human health. Therefore, we did not consider this option. Instead, we assumed increasing the price of conventional wines through taxes.

In Australia, alcohol taxation has a long history and changed many times. Currently, two systems are in place: one taxes beer and spirits based on volumes ('excise tax'), and another one taxes wine based on value ('wine equalization tax, WET) (Parliament of Australia 2015). WET is 29% of the final wholesale price of wine, which eventually is paid by consumers. With 10% Goods and Services Tax (GST) applied to retailers' margin, the total tax of a wine bottle is about 40%.

We propose four hypothetical scenarios in which WET increases by 17%, 21%, 52%, and 70% only on conventional wines. By doing so, WET changes from 29% to 35%, 40%, 45% and 50% level. We test these scenarios after the market saturation point, at week 150, when all the households purchased wine at least once and their wine preferences are known. Figure 3.3 represents how applying different taxation scales on conventional wines can change the ratio of organic wine purchasers.

By imposing additional taxes, the final price of AU$10 per bottle increases to AU$10.35, AU$10.71, AU$11.06, AU$11.42, respectively. This increases the ratio of organic wine consumers from 8.5% to 25% over 600 weeks. Research on wine price value shows that the demand for cheap wines is highly price-elastic (Hooke 2016), although there is little agreement about magnitudes. For example, the estimation of price elasticity for wine in France is 0.9-1, in the United States 0.44-1.654, and in World it is 0.7-1.11. Wine price elasticity in Australia is reported to vary between 1 and 1.8 (Tsolakis, Riethmuller & Watts 1983). Estimates of price elasticity of demand for wine confirm the validity of the trend we see in the simulation results.

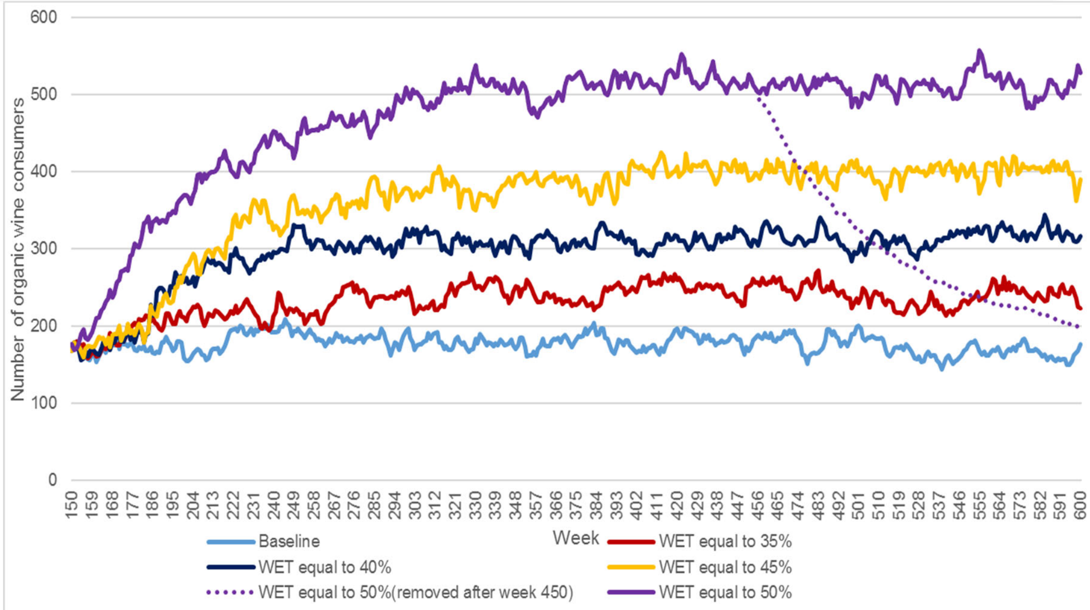

Figure 3.3. Comparing the diffusion of organic wine purchasing behavior among households in different scenarios of structural interventions. The dashed line indicates the dynamics of behavior when the 50% WET is removed after week 450

Notably, if 20% extra tax on conventional wine is removed at week 450, the percentage of organic wine consumers drops but stays slightly higher than the baseline (11% compared to 8.5%). Once new habits are formed, in response to changes in the price structure, they are likely to stay even after the measure is relaxed.

3.3.3. Persuasive intervention: informational marketing

Persuasive interventions aim to influence the attitude, perception, and norms of individuals and groups without changing the contextual-external factors. There are three types of persuasive interventions. The first type focuses on increasing individual knowledge to promote certain behavior, say, create positive attitudes toward green alternatives. Information campaigns are considered useful in communicating the pros and cons of alternatives (Steg & Vlek 2009). The second category aims at strengthening the PBC of consumers to act in a certain way, for example by motivating altruistic behavior when promoting pro-environmental actions, creating a commitment, and implementing individualized social marketing. Finally, the third category reinforces social norms by informing consumers about the behavior of others, role models, in particular. For environmental behaviors, which are easy, convenient and inexpensive to adopt (like wine shopping), the first category of informational strategies appears to be an effective motivational approach. Hence, we explore to what extent educating households and increasing their organic wine awareness can change the number of organic consumers.

Over the last 10 years, due to increased awareness about the negative impacts of alcohol, global wine markets have experienced a declining trend. The percentage of Australian everyday wine drinkers has significantly dropped from 20% in 2007 to 13% in 2017 because of an alcohol education program by the government (Wine Australia 2018). However, Australia has no comprehensive program to raise public awareness about organic food and drinks and still price, lack of trust, and lack of knowledge are among the top three barriers for buying organic food (Lawson, Cosby, Baker, Shawn, et al. 2018).

To understand what set of actions can promote organic wine awareness, we benchmark a successful program established in Sweden to educate people about organic products. Swedish people are globally known for their high per capita purchase of organic foods and beverages, and this trend is now apparent in organic wine consumption (Vin-Exchange Group 2018). In 2013, Swedish state alcohol monopoly, Systembolaget, aimed to increase the assortment of organic drinks to 10% by 2020 (Szolnoki & Borchert 2016). Since then, it has started to design and execute a set of programs toward raising public awareness around organic drinks and wine, in particular. Clearly labeling organic wines, providing organic alternatives for popular brands, pushing shops and hotels to offer more organic wines, employing organic wine experts, and training store staff were the main practices employed (Karlsson 2014). A special TV program, Kalla Fakta, about differences between conventional and organic wines had a big impact (Szolnoki & Borchert 2016).

Along with customers, Swedish monopoly has issued and passed a sustainable Code of Conduct for importers, and for producers. Systembolaget has already achieved 10% of organic sales volume in 2016, 4 years ahead of the proposed schedule (Systembolaget 2017). Despite having a small wine market with only five million regular wine drinkers, 51.2% have stated their preference for organic wine in 2017 (The DIVA Network 2017).

Inspired by this process, we propose two hypothetical scenarios where the health and environmental benefits of organic wine are advertised moderately or intensely. In terms of model parameters, this means that health concerns of household *i* at time t ($F_{Ai1}(t)$) is increased slightly (by a uniform distribution in the interval [0, 0.1]) or mildly (by a uniform distribution in the interval [0.1, 0.2]). In addition, agents learn about the environmental impacts of organic food and wine at a different pace depending upon their learning ability and the intensity of informational advertising. Household *i* acquires the knowledge, at the rate of intensity level times learning ability. As the environmental awareness of consumer *i* at time *t* grows ($F_{Ai2}(t)$), the probability of gaining a positive attitude toward organic wine increases.

Similarly, we initiate these scenarios after week 150, when the number of organic wine consumers levels off. Figure 3.4 presents how moderate and intense informational marketing can change the percentage of organic wine purchasers. Sustainable Brand Insight reported that through Systembolget sustainability programs, including education about sustainability issues and the risk of alcohol consumption, the number of Swedes who became aware and smart about socio-environmental issues has grown by 8% in just one year (Szolnoki & Borchert 2016). Our model output shows a 7% growth in the number of organic wine consumers (from 8.5% in week 150 to 15.5% in week 600). The consistency between model results and observed data confirms the validity of this model. This considerable growth in the ratio of organic users highlights the significant influence that media and education can have on increasing demands for sustainable products.

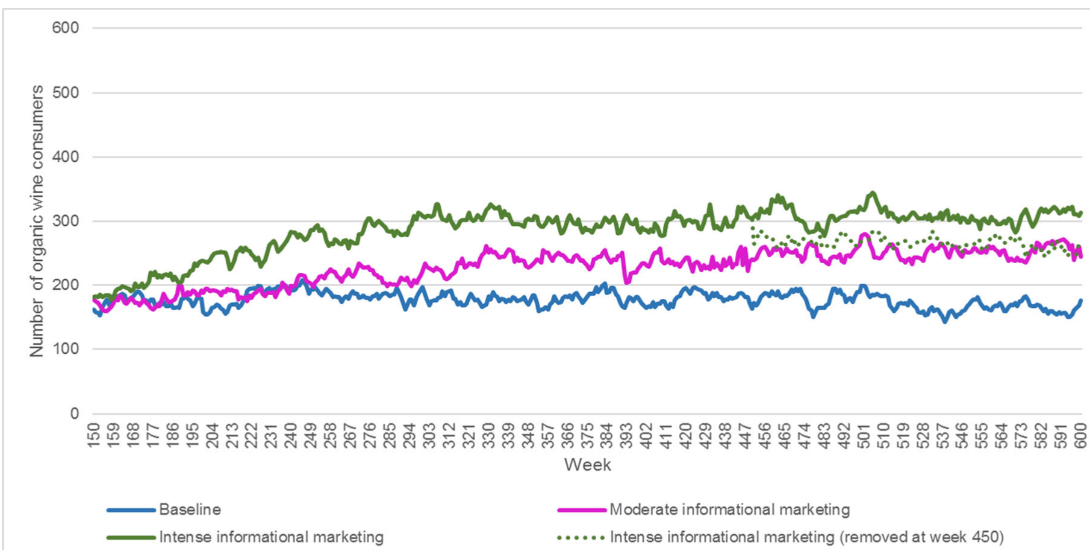

Figure 3.4. Comparing the diffusion of organic wine purchasing behavior among households in different scenarios of persuasive intervention. The dashed line presents the dynamics of organic wine consumers after the intense marketing program stopped

We then assume that the marketing program returns to a low-intensity level in week 450. The percentage of organic wine consumers remained 1.5 times higher compared to the baseline scenario (8% vs. 12%). Note that the drop in organic wine consumers after the informational intervention suspension (3.5% reduction) is considerably smaller compared to the tax suspension (20% reduction). In other words, the self-learning ability of households is greater than induced by informational strategies compared to structural strategies. It is not only the experience from wine shopping that helps the agents to learn but also the information about organic production that they continuously receive. This highlights that promoting context-dependent repetition of behavior in combination with sharing information about that behavior may shape lasting habits.

3.3.4. Combined intervention

According to Steg & Vlek (2009), to evaluate the effectiveness of an intervention, its singular influence should be compared to its influence in combination with others. They emphasized that combined interventions are more likely to be successful in changing behavior. Pro-environmental choices face both contextual and informational barriers while often interventions focus only on one of them. Additionally, different target groups have different motivational, habitual and contextual factors, so policy interventions should reach different audiences to make a significant impact.

Hence, we run a combined tax-marketing intervention and compare results with one structural and one information scenario with the highest effectiveness in changing behavior (see Figures 3.5 and 3.6). Our results indicate a 44% increase (from 8.5% to 52.5%) in the percentage of households with organic wine preference compared to the baseline. This is 28% higher than tax, 42% higher than informational marketing, and 20% higher than by applying these interventions, separately. The emergent effect from various interventions is non-additive, with the combined scenario exhibiting a nonlinear growth in the share of households preferring organic wine. The number of people with organic wine preferences continues to grow even after the forecasted period, reaching up to 1400 in week 1000.

These results highlight that:

(1) Behavioral shifts occur when the social pressure for purchasing conventional wine reduces. Jager & Ernst (2017b) suggest this phenomenon is caused by co-dependent behaviors, where individual behavior is amplified by its social environment. They state that "the coupling results in social processes that may become self-amplifying: the more people change, the stronger the social pressure on other people to change as well."

(2) A cascade of behavior changes for purchasing organic wine is triggered by getting over the 35% tipping point, which can be achieved only by combining two strategies. This radical change does not occur even if more than a third of the population adopt organic wine in response to separate interventions.

(3) Conformity rather than social learning plays the dominant role in purchasing contagious products, including wine. As organic wine purchasing behavior gains more

visibility, it is more likely to gain social approval. The norm for conventional wine purchasing in a vicious cycle can shift to organic wine purchasing in a virtuous cycle and get reinforced.

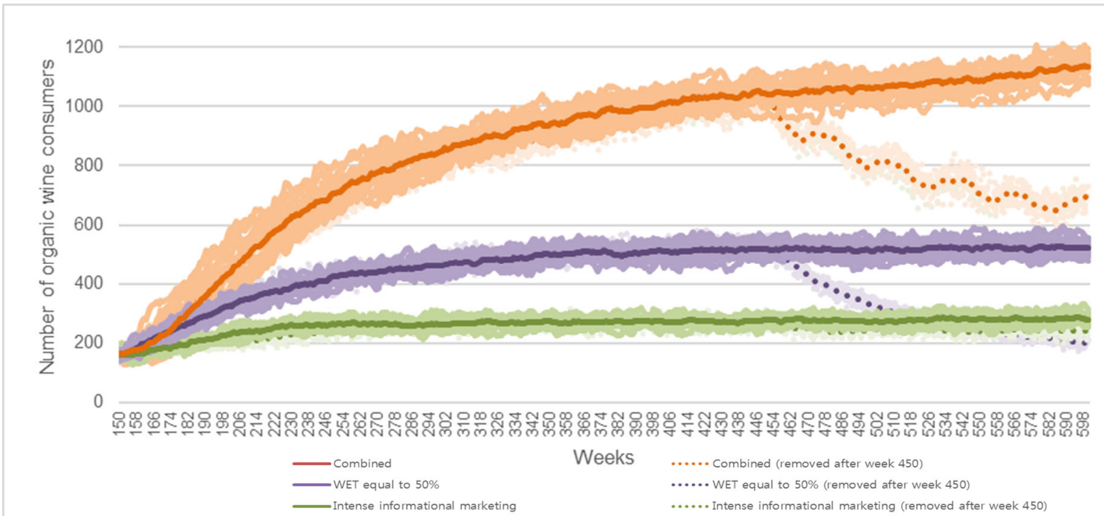

Figure 3.5. Comparing the diffusion of organic wine purchasing behavior among households following structural, persuasive and combined interventions (after 20 runs). Dashed lines present the dynamics of organic wine consumers after interventions are suspended

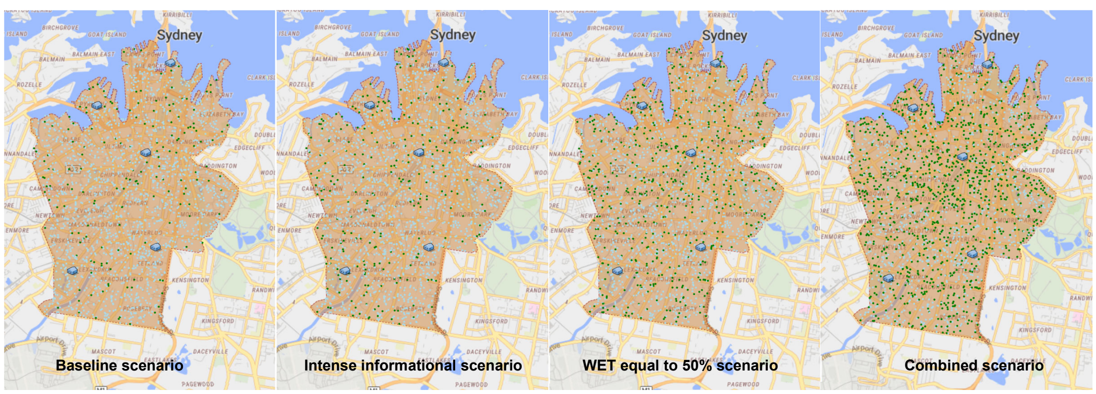

Figure 3.6. Comparing the spatial diffusion of organic wine purchasing behavior in three scenarios

Notably, the learning rate of households in the combined scenario (28.5%) is significantly higher than in the persuasive scenario (12%) and structural scenario (11%). Similar to the real-world, household agents learn proactively from the environment and accumulate previous shopping experience to do habitual shopping. These habitual behaviors tend to persist unconsciously and automatically. This shows how the model can be useful to identify what duration of intervention is sufficient to promote the context-dependent repetition of the behavior for habit formation.

3.4. Conclusions and implications

This paper focuses on the demand side of organic food market and quantifies the cumulative impacts of behavioral changes among heterogeneous consumers, prone to behavioral biases and social interactions. We take organic wines as an example, but the approach is transferrable to analyze other food markets where consumers choose between conventional and organic products. We develop a spatial ABM grounded in theory and data to understand wine purchasing behavior. The model could be a part of the extended supply chain framework (Taghikhah, Voinov & Shukla 2019a), that highlights the significance of raising consumer awareness and motivating behavioral shifts for reducing the environmental impacts of food production. We believe that the role of consumers and their preferences is an important factor in shaping the transition to a sustainable food supply chain.

Using ORVin, we explore the role of different policy interventions such as taxation and public awareness campaigns in promoting the demand for organic wine. A combined market and information-based policy is more effective in promoting organic wine preference than applying these policies separately. This non-additive effect of policies is an emergent property in this system and may be explained by undercover altruism. This niche market can be tipped to a critical mass of acceptance only in this combined scenario when more than 35% of the population switch to organic wine. This finding is important for increasing the adoption of organic vice products where the willingness to pay is profoundly lower than for virtue products, even with the same price premiums. Organic vice products suffer from negative quality inferences, which can be reduced in social consumption situations/environments (Mollen et al. 2013). Therefore, if the concerns for public self-image and norm conformance representing undercover altruism are alleviated, the number of organic vice consumers is expected to surge.

Although the examined strategies are hypothetical, they have real-world policy implications for the food and wine sectors. From a food marketing perspective, while big supermarkets and food companies push for launching alternative organic food products, the small market size, and low willingness to pay for them hamper their prosperity. To successfully promote organic vice product lines, a combination of price promotion and normative cues can create major change. Price promotions are effective in attracting new consumers. Cues promoting organic purchasing as a common norm manipulate people’s anticipation about possible reactions of others (conventional consumers) and allow them to make a moral choice.

From an agricultural perspective, the Australian Grape and Wine Authority is actively looking for new methods and technologies to enhance the sustainability of wine industry and improve resource management (Australia 2019b). They emphasize that organic is most likely to become a major competitive advantage in the international market. ORVin contributes to this debate, adding insights about how Australian consumers' interests in eco-friendly wines can help to expand the organic trend domestically. It also tells policymakers how to provide additional support for organic farmers by changing consumers' expectations about the wine choice of others. From the health perspective, ORVin can help designing programs for encouraging healthier lifestyles and reducing the health-environmental risks of wine drinking.

There are several limitations in our study calling for future research. So far, the model is largely based on theory and published data. As for other ABMs, we make simplifying assumptions about the real world system, which could be advanced. We assume that the same products, two types of wines, organic and conventional, are available across all retailers and that all their characteristics (taste, color, packaging, etc.) are the same, except for their price. Another limitation in ORVin is that the simulated decision of households is limited to purchasing either organic or conventional wines, while probably both wine types may be purchased at the same time. Finally, a broader range of data should be collected to initialize all the parameters with empirical data and avoid unnecessary biases so that a better calibration and validation can be performed. At the same time, since most of the decision factors incorporated in the models are common for various food types, we think that by applying a few changes in the model, it could also be used to explore the uptake of other organic products, not just wines.

3.5. Author contributions

Conceptualization: F.T., A.V., N.S., and T.F.; methodology: F.T., A.V., N.S., and T.F.; software: F.T.; validation: F.T., and N.S.; data collection: F.T.; writing—original draft preparation: F.T.; writing—review and editing: F.T., A.V., N.S., and T.F.; visualization, F.T.; supervision: F.T., A.V., N.S., and T.F.

Appendix 3.A: Introduction

Food production-consumption is one of the most energy and resource-intensive activities of modern civilization. It accounts for nearly 15-20% of the total global anthropogenic greenhouse gas (GHG) emissions (Woods et al. 2010) and has a significant environmental impact. Since the introduction of chemical fertilizers to viticulture in the 19th century, food production has significantly contributed to a wide range of environmental issues particularly those related to land and water. Organic agriculture as a part of the solution can largely reduce the overall environmental footprint of food production by eliminating the application of chemical fertilizers and pesticides and reducing energy use (Pizzigallo, Granai & Borsa 2008). The effectiveness of organic farming in vineyards has been demonstrated by increasing biodiversity and improving the quality of soils. Organic food is not only more environmentally friendly but also contains higher levels of nutrients compared to conventional, improving consumers' health and wellness. Despite the environmental and health co-benefits, few farmers take the financial risks of organic agriculture. For example in conversion to organic vineries, farmers face 20-30% reduction in grape yields influencing the profitability of farming and changing the price of final products.

Food production tends to keep growing to meet human nutritional needs. Expanding conversion of natural habitat to agricultural land is the main driver of global forest loss and species extinction. According to the 2019 IPCC report (Intergovernmental Panel on Climate Change 2019), an essential part of reversing losses and avoiding ecosystem collapse is changing diets, and in particular a transition to organic food production and consumption. There are examples of quite successful and productive organic farmlands, where species richness and diversity is substantially higher than in conventional systems (Wilbois & Schmidt 2019). While organic farming provides a more sustainable solution to some of the ecological challenges in agriculture, it usually produces lower crop yields in comparison to their conventional counterparts, which results in higher food prices. Consumer food preferences and choices can be the turning point factor, where higher interest for organic diets can motivate farmers to adopt organic farming practices (Wheeler 2008). Organic diets have been convincingly exposing consumers to fewer chemicals associated with human diseases such as cancer, autism, and infertility (Hyland et al. 2019). Therefore, by purchasing organic food, people not only subsidize eco-friendly agriculture but also improve their health and well-being.

In 2018, the global sales of organic food reached US$ 89.7 billion, a 10% increase on the previous year. The United States has the most abundant organic market by value (Mosier & Thilmany 2016). Germany, France, Italy, and Spain have already started their organic consumption-production movement turning Europe into the second important organic food market. Despite the efforts to promote organic farming adoption, according to the International Federation of Agriculture Movements only 1.4% of the global farmlands are managed organically in 2019. Consumers as the central change agent play an essential role in the transition towards sustainable food systems. While they are now more aware and conscious about the environmental issues compared to the last few years, the average share of organic food spending remains low (Lawson, Cosby, Baker, Shawn, et al. 2018).

There are a number of reasons for the lower interest in the purchase of organic food. According to a recent Australian organic market report 2018, higher prices, lack of trust, and lack of knowledge are identified as the top three barriers of organic purchases. In general, Australians do not considerably value organic products over conventional products, are not willing to pay higher food prices for sustainability features, and are much less willing to pay premium prices for organic food (Lockshin & Corsi 2012). As a result, farmers failing to receive premiums lack the motivation to continue their organic farming since consumers do not value and appreciate the benefits of organic products. Many policies are already in place to promote organic food consumption; however to what extent and in what ways they lead to changes in preferences and how they define the future development of the organic sector is unknown.

Empirical research on organic food preferences, so far, could not provide a clear understanding of the extent of interventions that can influence the behavior of consumers (Tait et al. 2019). The effectiveness of designed interventions has to be monitored over extended periods of time while experimental assessments fail to consider long-term effects (Bernabéu, Prieto & Díaz 2013). In many cases, running an experiment can take considerable time, costs and efforts before reaching the desired results, if reaching them at all. In experimental statistical studies of consumer wine preferences, the impact of social interactions between individuals on the choice of wine is largely disregarded. Empirical data alone hardly provides information about the implications of wine consumption reasoning for the patterns that are seen on the regional and national levels. The paradoxical inconsistency remains: while 40% of consumers worldwide are interested in health and environmental benefits of organic wine (Loose & Lockshin 2013), the global organic wine market share is lower than 10% and only 5% of the World's vineyards are organically certified. These limitations emphasize the need for methods that complement the empirical information about the complex behavior of organic consumers.

Vice and virtues are typically defined relative to one another. Vice food or “wants” refers to products that are relatively more gratifying and appealing in the short term but have negative health impacts in long-term consumption such as chocolate, chips, wine. On the contrary, virtue food or "shoulds" may not possess the hedonic allure of vices or immediate pleasurable experience but provides utilitarian benefits such as apple, vegetable, green smoothie. Generally, consumers are highly motivated to consume more vice food rather than virtue food. Researchers have indicated that organic labels of vice and virtue food types may cause different responses in consumers (Muñoz-Vilches, van Trijp & Piqueras-Fiszman 2019). On the one hand, Van Doorn & Verhoef (2011) report that consumers pay more price premiums for organic virtue food in comparison to vices due to negative quality connotations for vice products. On the other hand, Lee et al. (2018) show mixed results, where the organic label on vice food both increases and decreases food intake depending on the consumers' characteristics. They declare that consumers' perception of external and internal health control is the mediator factor in decisions between organic and conventional counterparts. While in health externals, organic vice food provokes a guilt-reduction mechanism and increases the willingness to purchase, it reduces the intake of internals. The choice of organic in vice and virtue products is still an on-going topic calling researchers for further studies (Hidalgo-Baz, Martos-Partal & González-Benito 2017).

System models can improve our understanding of the complexity of food purchasing decisions, and to further interpret and forecast it. Models are useful for designing interventions, comparing policy options, testing theories, and scaling behavioral patterns observed in experimental and field data. While statistical approaches are strong in revealing patterns in data, modeling methods such as agent-based modeling (ABM) add value by exploring causal connections behind system-level phenomena and patterns. ABMs not only study macro-level patterns emerging from actions of heterogeneous agents and their interactions with each other but also show the downward causation where the behavior of individuals at the micro-level influenced by the collective actions (Jager & Ernst 2017b). This makes ABM a suitable method for studying the complexity of cumulative market effects of individual behavior changes, especially for food preferences where considering social norms can lead to a high level of uncertainty about future behaviors.

ABMs are getting popularity for encouraging behavior change in the context of marketing, food, health, and ecology. Hu et al. (2018) examine the impact of promotional and marketing activities on consumer preferences. Li, Zhang, et al. (2018) develop a model for assessing the impact of access and price on New York's fruits and vegetable consumption. Garcia, Rummel & Hauser (2007) address validation issues for ABM in the field of marketing focusing on wine industry case study. Regarding environmental issues, there is recent research studying behavior change in energy markets (Niamir et al. 2018), low-emission cars (Kangur et al. 2017), waste management (Rangoni & Jager 2017), climate adaption (Erdlenbruch & Bonté 2018), and land use (de Koning, Filatova & Bin 2019). Yet, the impact of behavior change interventions on consumer preferences for food with sustainability characteristics are scarce. We address this gap by developing an ABM – ORganic Vine (ORVin) – to simulate the decision-making process and explore the key stimuli that lead people to make choices between organic and non-organic wines in the complex shopping environment.

This paper aims to explore the cumulative market consequences of individual consumer choices influenced by behavioral biases and social influence. To gain insight into the process of organic wine consumption, we consider the Theory of Planned Behavior (TPB) (Ajzen 1985) along with the Alphabet Theory (Zepeda & Deal 2009) and the Goal Framing Theory (Lindenbrg & Steg 2013). TPB is the most utilized theoretical framework to measure organic food purchasing intention (Guido et al. 2010). The second and third theories are used to examine the role of psychological (e.g., habitual purchasing) and functional (e.g., contextual-environmental cues) factors on organic food consumption. This provides a solid theoretical framework for identifying cognitive and product-related factors (beliefs, attitudes, norms, habits, and goals) that may influence organic wine purchases. While prior literature attempted to explore the consumer intention for organic food, the barriers between organic food purchasing intention and behavior have been far less studied (Kushwah, Dhir & Sagar 2019). Appendix B extensively explains how we conceptually connect these theories to understand the decision-making process in the wine context.

The Australian wine industry is comprised of over 6,000 vineyards, approximately 2,500 winemakers, and more than 175,000 people contributing $AU40 billion to the economy annually. In 2018, 135,000 hectares of land across the country, mainly in Southern Australia, is used to produce 1.29 billion liter wine, most of which (around 65%) are exported at $AU 2.8 billion. Currently, less than 0.5% of grape production volume in the country belongs to organic wine, with the total organic area under vine surpassed 400,000 hectares in 2017 (Wine Australia 2017). Most of the certified organic wines are exported to Europe (78%, including Sweden, UK) and the United States (12%). Despite the growing interest in the global market, still, organic wine remains a niche segment in the domestic market of Australia.

We apply the model to the case of the Sydney Metropolitan Area by incorporating the results of a published survey about the wine preferences of 2099 heterogeneous households. The innovative contribution of this paper is two-fold. Firstly, we develop an ABM to advance knowledge about the effectiveness of behavior change policy instruments on diets by explicitly considering consumer perceptions of and preferences for organic products. Within the scarce modeling literature on behavioral change towards sustainable food, this is the first simulation model proposed to understand bottom-up choices between organic and non-organic wine and the policies that can impact them. Secondly, we explicitly trace the effects of social interactions, drinking habits and desirability factors on wine consumption behavior. Regardless of its taste, wine is greatly associated with festivity, fraternity, social norm and rarely consumed alone. Previously, social norms have not been considered as a factor for wine consumption behavior, yet they strongly influence how consumers choose organic products. Thirdly, this model can open new research avenues for understanding how to persuade consumers to make healthier choices, when dealing with vice products such as wine. Because organic wine is hardly perceived to be of higher quality than conventional wine, it is considered as an exception to the subjective norm.

Appendix 3.B: Theoretical framework for studying behavior change

Environmental psychology conceptualizes pro-environmental behavior through a number of theories. Steg & Vlek (2009) and Groening, Sarkis & Zhu (2018) offer extensive literature reviews on consumer behavior theories for green products. The Theory of Planned Behavior (TPB) by Ajzen (1985) is important to understand behavioral change. According to TPB, a particular behavioral choice is preceded by intention, which in turn is influenced by individual’s behavioral, normative and control beliefs (Ajzen 1985). Behavioral beliefs affect individual attitudes toward a particular behavior. In contrast, normative beliefs are shaped by opinions and expectations of key people in person’s social network, leading to the emergence of subjective norms. Lastly, control beliefs reflecting individual’s perceptions of own control power over a choice or situation configure the perceived behavioral control (PBC). We use TPB as the basis for explaining the wine purchase behavior.

TPB is useful to explain how “intentions” shaping consumers’ behavior form. Yet, an intention to act may not always lead to the actual behavior. Factors such as cognitive inhibition, action control, habitual response, and other behavioral biases may interfere

(Sniehotta, Scholz & Schwarzer 2005). In some cases, the environmental conditions can motivate or hinder an action, or behavioral heuristics may act to replace reasoning. Yet, TPB pays scarce attention to these mediating factors between intention and actual behavior and may face limitations when comprehending a consumer choice between organic and non-organic products. Our theoretical framework enriches TPB by perming habitual behaviors, which are heuristics with low cognitive involvement in decision-making, and by explicitly accounting for conditional external factors that are out of individuals' control (Fig 3.B1).

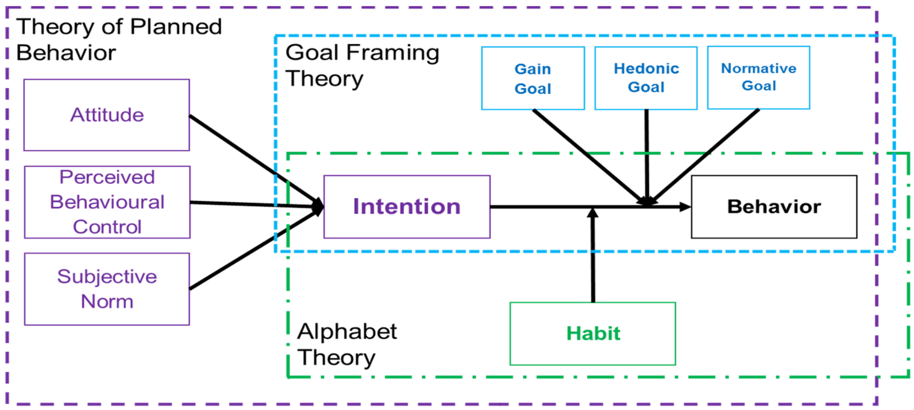

Figure B1. Proposed theoretical framework for understanding wine consumer behavior

In evidence-based research, Gardner (2015) defines habit as "*a process by which a stimulus automatically generates an impulse towards action, based on learned stimulus-response associations*." Habit and behavior are interrelated personal characteristics: habits are shaped by repeating particular behaviors and creating habitual behaviors. In Ajzen's TPB, the impact of habits on the mechanism of decision-making is disregarded; whereas, the unthoughtful repetition of actions or habitual behavior does not require supporting intentions (Lally & Gardner 2013). According to Triandis (1977), intention drives the behavior only when it is new, unlearned, and untried; however, old, well-learned and repetitive actions are likely to be controlled by habits. In an experimental study, Ji & Wood (2007) test the relationship between habits and behaviors in three case studies including taking fast food, watching television news, and riding a bus. Their results show that when the habits are weak or moderate, the individuals' behavior is mostly predicted by their intentions but when the habit is strong, intention loses its influence on behavior. Therefore, strong habits drive people to pursue actions regardless of their intentions (Ji & Wood 2007). To account for this mediating role of habits, we employ the Alphabet Theory (Fig 1). This theory is strong in explaining how the habitual behavior of individuals can mediate the relationship between intentions and actual behavior (Zepeda & Deal 2009).

The external conditions and the interactions between humans and their environment can explain why intentions may not end up to form a behavior (Schäufele & Hamm 2017). Contextual factors are considered as interferers that can directly or indirectly influence behavior (Steg & Vlek 2009). As an example of direct impacts, one cannot use public transport if the infrastructure, trains, or bus services are not available. The indirect effects of conditional factors are analyzed from two aspects; either context-behavior relationship is mediated by intention, or intention-behavior relationship is mediated by context. The latter aspect stands valid for organic wine consumption behavior (Schäufele & Hamm 2017). The Goal-Framing Theory (Lindenbrg & Steg 2013) assists researchers in explaining how environmental conditions – such as price or expressive signs addressing a particular norm, e.g., posters showing the diseases caused by smoking cigarettes – influence behavior. This theory distinguishes three overarching goals to frame the behavior of a person. These goals include the hedonic goal, to create a better feeling of enjoyment, the gain goal, to improve and protect personal resources, and the normative goal, to act appropriately for the group (Lindenberg & Steg 2007). Goal-framing theory proposes that for every person, one goal is focal, and the other goals are in the background either encouraging or discouraging the focal goal. Although each person holds three goals at the same time, the activated goal drives their way of thinking, sensitivity to information, and information processing for decision making. In many cases, hedonic goal-frame is the strongest; however, external conditions may increase the strength of the normative goal-frame to shift the focus. For example, in the classic study of paying at coffee or tea dispensers, replacing a picture of a flower with a picture of eyes looking at the customer triples the payments (Bateson, Nettle & Roberts 2006). Lindenberg & Steg (2007) conclude that hedonic and gain goals can push the normative goals aside if social values are not supported properly. Here we use the Goal Framing Theory to account for the influence of external conditions on an individual purchasing decision.

Appendix 3.C: ORVin model description

The model developed for this study, ORVin, employs agent rules that are grounded in the above described theoretical framework. To describe this system, we use Overview, Design, and Details (ODD), a standard protocol developed by Grimm et al. (2006) for documenting and communicating ABMs. It facilities model replicability and reproducibility through supporting complete and understandable descriptions.

3.C.1. Model Overview

3.C.1.1. Purpose

Based on theoretical and empirical considerations, ORVin is developed to understand consumer purchasing behavior regarding organic wines. To gain insight into the process of wine consumption, the theory of planned behavior is considered along with alphabet theory and goal framing theory. This provides a solid theoretical framework for identifying behavioral factors, including beliefs, attitudes, norms, habits, and goals that may influence organic wine purchases. The model can be used to examine the effectiveness of different interventions for encouraging households to purchase organic wine instead of conventional wine. ORVin provides a dynamic platform to study the individual reaction of the disaggregated, low-level actors of the system to the hypothetical changes in the wine market such as taxation, marketing campaigns, and promotions. The cumulative impacts of changing behavior are also evaluated with respect to the environment. This model improves users' understanding of the complexity of wine purchasing decisions and helps them to interpret further and forecast organic wine market.

3.C.1.2. Entities, State Variables, and Scales

This model simulates the behavior and interactions between two agent classes: households and wine retailers. It is, in particular, used for exploring household preferences for organic wine in the City of Sydney Local Government Area, Australia. The City of Sydney is approximately 26.15 square kilometers and is home to over 103,844 estimated households with an average size of 2.2 in 2016 (Sydney 2016).

A number of attributes characterize households[3]: (1) head of household gender, (2) head of household age, (3) household size (i.e., number of household members over 18 years old), (4) average income level, (5) highest education level, (6) head of household ability to learn (i.e., capacity of understanding new concepts, a type of intelligence), (7) geographic coordinates of residence, (8) wine shopping frequency, (9) number of bottles per purchase, (10) willingness to pay for organic wine (considered in dollar value), (11) maximum allocated budget for a bottle of wine, (12) wine knowledge (the health and environmental considerations of organic food and wine), (13) action repetitions which is the number of times an action should be repeated before it becomes a habit, and (14)

[3] The head of household means a person who normally does the wine shopping in the household.

frequency of revisiting PBC and social norms. For shop agents, we only consider two attributes 1) location and 2) wine types on sale and their prices.

For this model, two sets of control variables are defined. Users can change variables such as (1) price of products, (2) tax rate, (3) and, level of informational marketing activities (i.e., awareness and knowledge about organic wine). The production rate of organic and conventional wines and the delivery time of products are static.

ORVin is programmed in AnyLogic Software and will be available for interested researchers upon request. Most of the households report shopping wine at least once per week and thus, the time step in the model is set to one week. The simulation runs for 600 weeks, but this can be easily changed. Snapshots of the model interface at setup and during simulation are illustrated in Figure 3.C1 and 3.C2, respectively. A map of the City of Sydney is displayed in the model environment and all agents are placed on it (marked in orange). The organic and non-organic households are depicted as green and light blue dots, respectively, and blue houses represent five major wine retailers in the region.

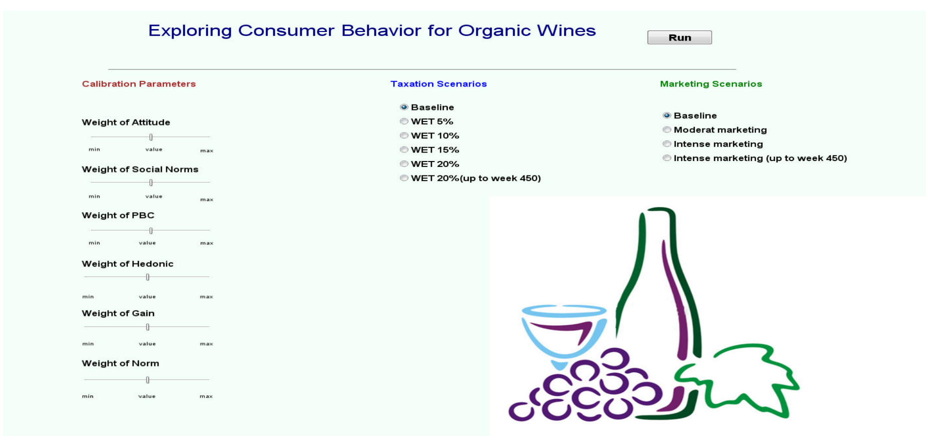

Figure 3.C1. Model interface at set-up. Here, some of the model parameters and scenarios can be defined.

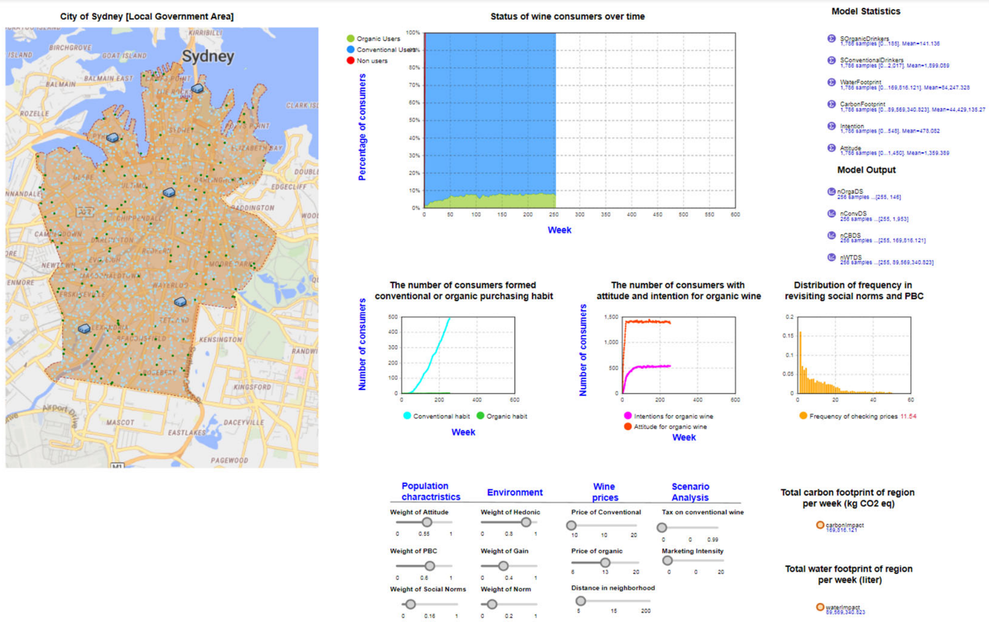

Figure 3.C2. Model dashboard during run time. The map of the area is presented as well as the main model outputs. A number of sliders are provided to change system performance on the fly.

3.C.1.3. Process Overview

The wine shopping journey for the head of a household is schematically shown in Figure 3.C3. They can either purchase organic or conventional wines. Based on their shopping frequency, shoppers list the available wine retailers and visit the closest one. At the beginning of the simulation, households have no preference for organic or conventional wine. When they arrive at the retailer, they first check which wine types are in stock and then compare their prices with each other and with their maximum allocated budget for wine. They choose a wine type based on a set of behavioral factors that are not based on pure rationality. Within each shopping event, four modules/ phases are processed in the following order: intention, habit, goal, and purchasing behavior (see section 3.C.2 for details). If the price of wine is higher than the households' spending limit or if no suitable wines are in stock, they leave the shop without making any purchase.

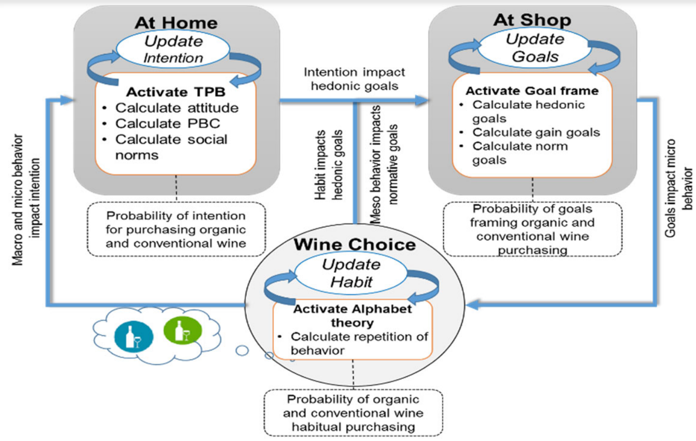

Figure 3.C3. Household wine-related decision-making process.

Households make planned purchase decisions between organic and conventional wines, according to TPB, at home. Every time they go shopping for wine, they list the available wine retailers and visit the closest one. We assume that the retailers always meet the market demand, and no stock-out condition is allowed. The choice is made between organic or conventional wines at the shop according to the goal framing theory. The frequent wine shopping, personal norm, activates alphabet theory to consider habitual purchasing and its effect on decisions. The dynamics of changes in the wine preference of consumers emerge from the household behavior, while we impose probabilistic theoretical/empirical rules on them. Different control factors, such as the price of wines and organic informational-educational campaigns, drive changes in the behavior of wine consumers. Emergence can appear if we find that combining various control factors, we may be producing effects that go beyond adding the impacts in individual factors.

3.C.2. Design Concepts

3.C.2.1. Emergence

The dynamics of changes in the wine preference of consumers emerge from the household behavior, while probabilistic theoretical/empirical rules are imposed on the behavior of each household. Changes in the behavior of wine consumers are driven by different control factors such as the price of wines, and organic informational-educational campaigns. Emergence can appear if we find that combining various control factors we may be producing effects that go beyond adding the impacts in individual factors. For example, the effect of changing wine pricing while running an educational campaign can be more (or less) substantial than when we enact these strategies separately.

3.C.2.2. Adaption

On the one hand, households exhibit a set of adaptive behaviors in response to different stimuli. An important adaptive process considered for all households is learning. Once individuals are exposed to informational messages, they tend to increase their awareness about that matter and adjust their attitude accordingly. They will gradually forget newly learned information if it is not repeated. Informational marketing also influences individuals' goal-frame. Changes in price and availability of wines lead to changes in perceived behavioral control (PBC) and eventually intention, and goal-frame. Finally, habit is another adaptive behavior defined for households and is highly dependent on time and context. In the real world, humans learn by repeating an action and gaining experience. This experience emerges as a part of wine purchase decision. On the other hand, wine producers regulate the production amount considering the demand and price of organic and conventional wine. In other words, producers/retailers respond to the households' wine decisions by increasing or decreasing production rates. We assume that the retailers always meet the market demand and no stock-out condition is allowed.

3.C.2.3. Interaction

The social network of each household includes neighbors, households living up to 400-800 meters away from them, and wine shoppers at the retailer. The defined neighborhood type and buffer may influence the estimation of neighborhood effects (i.e., the effect of a particular neighborhood characteristic on wine choice) (Duncan et al. 2013; Hwang, Hurvitz & Duncan 2016). In social interactions, households exchange information about wine preferences and continuously update their perceived subjective norms about wine types.

3.C.2.4. Stochasticity

Due to uncertainty in data, the initial conditions of several parameters are determined as stochastic values. The stochastic parameters involved in the model are:

- Wine shopping basket size, which is the number of bottles the household purchases per shopping trip, follows a uniform distribution over the interval [1,5] bottles;
- Maximum money to be spent on a bottle of wine is uniformly distributed in the interval [30,100] dollars;

- Leaning capacity, which indicates memory, attention and the speed of processing data in households is assigned random numbers uniformly distributed over the interval (0.0001,0.005), where 0.0001 indicates a slow learner while 0.005 indicates a quick learner;
- Depending on the number of times a household purchases wine and their habits, three uniform distributions are assigned to the probability that a household revisits their preference for organic wine (i.e., checking the price of substitute wines and observing the wine choice of the neighbors). Within the first 4 shopping events, the frequency of checking the price of alternatives and the wine preference of neighbors is considered as a random number uniformly distributed between 1 and 4 (i.e., PBC and social norm are updated every 1 to 4 weeks). In the next 5 to 22 shopping events, as agents gain experience with purchasing wine, they check the prices and other preferences for wine less often (a uniform distribution bounded between 5 and 22 is used). Once a household gets used to a particular wine type (i.e., either organic or conventional wine habit is formed), this frequency of updating PBC and social norms reduces to once every 23 to 51 shopping events (a uniform distribution on the interval [23,51]);
- Elements involved in predicting attitude (such as health concerns, awareness about organic wine, and willingness to change) and PBC (perceived value of organic wines) are interpreted as probabilities (refer to section 3.C.3.3 for more details);
- A triangular distribution that takes on numbers between 18 and 254 with mode 66 is assigned to the action repetition attribute indicating the minimum number of times households should purchase a particular wine type before this preference becomes a habit. In addition, a uniform distribution is used for presenting the strength of habits (refer to section 3.C.3.3 for more details).

3.C.2.5. Observation

During the simulation, the model calculates the statistics (maximum, minimum, average, standard deviation) of organic and conventional wine consumers per week as well as the relevant the overall amount of carbon and water footprints across the period. The number of households with positive attitudes and intentions towards organic wine are presented for calibration and validation purposes. In addition, the number of households who have habitual wine purchasing behavior and the distribution of frequencies households revisit the price of substitutes and other norms are considered.

3.C.3. Model Details

3.C.3.1. Initialization

For initializing the model, a population of 2099 households is randomly distributed over the City of Sydney. We locate one wine retailer for each of five major suburbs of this area according to a Google map. The shops are assumed to sell similar wines for the same prices (there is no difference between the wine shops in the model). We discuss in 3.C.1.2 the exact values of state variables based on data and in 3.C.2.4 the initial values chosen arbitrarily. Since some of the initial values are set stochastically, the model initialization is not always the same and it varies between simulation runs.

3.C.3.2. Input Data

For household agent parametrization, we use the results of Ogbeide (2013a) field experiment on Australians' interest in organic wine. He used a sample of 2099 responses (representative of the Australian population) to understand the factors affecting the willingness to pay for organic wine. The details of the initial values obtained from field experiments are listed in Table 3.C1. The correlations between gender and household age, income, and education level are considered.

Organic and conventional wine prices are set based on data provided by the Australian Government via Wine Australia Website (https://www.wineaustralia.com/). In order to reap a 50 percent profit margin, conventional and organic wines are retailed at minimum AU$10.00-13.00 (approximately US$8-10) per bottle, respectively (taxes included). These base prices are also used by Ogbeide, Ford & Stringer (2015) for exploring the Australians' willingness to pay premiums. Wine Australia reports that people are willing to pay 20-30% more for a bottle of organic wine. We assume that the selling price of wine at farmer doors and retail stores are the same. In real markets, wines at cellar doors are usually cheaper (by at least 20%) than in bottle shops.

Table 3.C1. Field experiment data from (Ogbeide 2013a)

Gender	**%%**	**Income**	**%%**	**Household size (above 18)**	**%%**
Male	61.5	Less than 50,000	31.8	Single	14.5
Female	38.5	50,001-100,000	62.6	2	56.3
Age	**%%**	More than 100,001	27	3	15.81
18-34	17	**Education**	**%%**	4 and more	13.33

35-54	41.7	School-High school	26.8	**Willingness to pay for organic wine**	**%%**
55 and more	41.3	Diploma-Bachelor	62.6	0-10%	15
Frequency of wine consumption	**%%**	Master-Doctorate	10.6	10%-20%	15
Everyday	16.48	**Wine Knowledge**	**%%**	20%-30%	22
A few times a week	44.35	Relatively low	4	30%-40%	12
Once a week	23.73	Medium	64	40%-50%	8
Once a fortnight	8.48	Relatively high	32		
Once a month and more	6.96				

3.C.3.3. Sub-Models

Here, we include a more detailed explanation of the decision-making processes of our household agent (an overview is presented in 3.C.1.3). A list of all notations used in sub-models is provided in Table 3.C2.

Table 3.C2. List of notations used in the model and their description

Variables	**Definition**
F_{Ai1}(t)	Household i health belief at time t
F_{Ai2}(t)	Household i environmental awareness about organic wine at time t
F_{Ai3}(t)	Household i wine drinker types at time t
F_{Ai4}(t)	Household i willingness to change at time t
W_{A1}	Weight of health belief
W_{A2}	Weight of organic awareness
W_{A3}	Weight of type of drinker
W_{A4}	Weight of willingness to change
F_{Ai}(t)	Household i attitude at time t
F_{Pi1}(t)	Household i perceived economic value of organic wine at time t
F_{Pi2}(t)	Household i perceived availability of organic wine for at time t
W_{P1}	Weight of price
W_{P2}	Weight of availability
F_{Pi}(t)	Household i PBC for organic wine at time t
F_{Spoi}(t)	Total number of household i 's neighbors with organic wine preferences at time t
F_{Spi}(t)	Total number of household i 's contact network at time t

F_{Si}(t)	Household i subjective wine norm at time t
W_S	Weight of subjective norms
W_A	Weight of attitude
W_P	Weight of PBC
F_{Ii}(t)	Household i intention for wine at time t
NE_i^o(t)	The number of times household i purchased conventional wines at time t
NE_i^c(t)	The number of times household i purchased conventional wines at time t
H_i^o(t)	Households i habitual purchasing of conventional wine at time t
H_i^c(t)	Households i habitual purchasing of conventional wine at time t
FH_i^o(t)	Household i hedonic goal for organic wine at time t
FH_i^c(t)	Household i hedonic goal for conventional wine at time t
FG_i^o(t)	Household i gain goal for organic wine at time t
FG_i^c(t)	Household i gain goal for conventional wine at time t
F_{Sqoi}(t)	The ratio of conventional wine shoppers to total wine shoppers with household i at shop j at time t
F_{Sqci}(t)	The ratio of organic wine shoppers to total wine shoppers with household i at shop j at time t
FN_i^o(t)	Household i organic wine normative goal at time t
FN_i^c(t)	Household i organic wine normative goal at time t
W_N	Weight of normative goal
W_H	Weight of hedonic goal
W_G	Weight of gain goal
GO_i(t)	Household i organic wine goals at time t
GC_i(t)	Household i conventional wine goals at time t

❖ Intention

As shown by previous research, three main factors, including attitude, social norms, and perceived behavioral control determine the intention of agent i. Agents are different in terms of attitude towards organic food, willingness to pay more for organic wine as well as social network size. According to Squazzoni, Jager, & Edmonds (2013), these differences can generate heterogeneity in the population. WA, WP, WN indicate the relative importance of individual preference, social influence and contextual factors on the intention of agents for wine-related decisions. These weights are determined by model calibration, but this does not mean at all that the agents have the same intention. A similar rationale can be found in the study of Kniveton, Smith, & Black (2012) and Scalco et al. (2017) where these weights are determined by a regression method. In addition, our model focuses only on the City of Sydney Local Government Area, which encompasses only a few suburbs of the great Sydney. This spatial scale (Local Government Area) is one of the smallest socio-economic subdivisions in the Australian Bureau of Statistics. So, we assume that there are no significant differences between the suburbs of this statistical region (with regards to the weights of factors).

Attitude: Schäufele & Hamm (2017) reported demographics and information/knowledge-seeking as two main factors influencing the consumer attitude toward wine with sustainability attributes. Regarding demographics, researchers partially agreed that gender and income are two important characteristics determining the organic wine choice (D'Amico, Di Vita & Monaco 2016). Females with higher income levels have a more positive attitude towards purchasing organic wine. Regarding the relationship between age and organic wine purchasing attitude, the findings are conflicting. While some researchers reported no correlation between age and attitude to buying organic wine (D'Amico, Di Vita & Monaco 2016), others found a higher willingness to pay in younger people (Bernabéu et al. 2008; Sogari et al. 2015). Research on the food preference of Australians indicates that millennials are more willing to purchase a range of organic products (including wine). Their growing interest in organics may be explained by their higher concern for individual and family health, diet and food quality (Lawson, Cosby, Baker, Shawn, et al. 2018). Aertsens et al. (2011) showed that highly educated people have a higher level of knowledge about organic farming and environmental/health issues. Therefore, a high level of awareness encourages a positive attitude towards buying organic food.

In a series of exploratory studies, Melo et al. (2010), Melo, Delahunty & Cox (2011), and Melo et al. (2012) studied the relationship between wine drinking history and attitude towards wine to predict the future wine consumption pattern. Based on drinking frequency they categorized wine consumers into low, intermediate and high consumption groups. Lowe and intermediate consumption groups drink less than 933 ml/week (approximately 5 wine bottles/month) and from 933 to 2000 ml/week (between 5 and 10 wine bottles/month), respectively, whereas, high consumption group takes more than 10 bottles per week (above 2000 ml/week). For low consumption group, personal reasons for drinking (e.g., coping with tension, enhancing mood) are not a priority. They rather consume wine as a part of social life and are inspired by occasions and social events (e.g., gathering, gift giving) (Melo et al. 2010). Boncinelli et al. (2019) highlight that organic attitude of social drinkers is relatively greater than both moderators and high drinkers.

The willingness of people to change their choice is another factor influencing the attitude (Harmon-Jones & Mills 1999). The theory of cognitive dissonance (Festinger 1962) explains that once the intention and behavior are inconsistent, a willingness to change will arise. People experiencing an inner inconsistency or discrepancy (a distance between intention and behavior) tend to change either their intention or behavior depending upon their strength. The closer the distance of intention and behavior, the higher the resistance to change a behavior one faces (Jager & Mosler 2007). In our model, we assume that for households who have a willingness to change, the behavior is stronger than intentions.

Consumer attitude is defined as follows:

$$F_{Ai}(t) = W_{A1}F_{Ai1}(t) + W_{A2}F_{Ai2}(t) + W_{A3}F_{Ai3}(t) + W_{A4}F_{Ai4}(t); \qquad (3.C1)$$

where $0 \le F_{Ai1}(t),\ F_{Ai2}(t), F_{Ai3}(t), F_{Ai4}(t), F_{Ai}(t) \le 1$; $\quad 0 \le W_{A1}, W_{A2}, W_{A3}, W_{A4} \le 1$;

$\sum_{i=1}^{4} W_{Aj} = 1$; $\qquad$ i=1, …, n.

$F_{Ai1}(t)$ is the health concern of household i at time t, and is a function of their age, gender, and income level. $F_{Ai2}(t)$, organic wine awareness of household i at time t, is a function of education and wine knowledge. $F_{Ai3}(t)$ determines which drinker type household i is at time t by calculating the average number of drinks the household members have per week. $F_{Ai4}(t)$, is the estimation of household i willingness to change at time t. This parameter is utilized to assess the strength of disagreement between intention and behavior. In all presented formulas, n is the total number of households. We assign almost equal weights to health concern (W_{A1}weight of health concern), wine awareness (W_{A2}weight of organic awareness), and drinker type (W_{A3}weight of type of drinker), and a considerably smaller weight to willingness to change (W_{A4}weight of willingness to change). Equation C1 evaluates the attitude of individual i towards organic wine at time t. The values of all attributes and weights used in the formula are set up between 0 and 1, to make the outputs comparable. The sum of the weights is equal to 1.

Perceived behavior control: In predicting the perceived ease and difficulty of organic wine purchase, two critical elements are price and availability. A recent study on the relationship between organic wine and price found no that certified organic does not necessarily receive a price premium (Abraben, Grogan & Gao 2017). Lawson, Cosby, Baker, Shawn, et al. (2018) consider price as the main barrier to purchasing organic products in Australia. The conjoint analysis studies on food revealed that increasing the availability of organic food at shops could create a higher preference for healthy food consumption (He, Tucker, Gilliland, et al. 2012; He, Tucker, Irwin, et al. 2012). Similarly, for organic wine shopping behavior, availability is noted as a comparatively less influential factor in purchasing organic food for Australians (Lawson, Cosby, Baker, Shawn, et al. 2018). Among the entire hindering factors for purchasing organic products, price is the main issue while availability is listed fifth (Lawson, Cosby, Baker, Shawn, et al. 2018).

The described elements interact as in:

$$F_{Pi}(\mathrm{t}) = W_{P1}F_{Pi1}\ (t) + W_{P2}F_{Pi2}\ (t); \qquad (3.C2)$$

where $0 \leq F_{Pi1}(\mathrm{t}), F_{Pi2}(\mathrm{t}), F_{Pi}(\mathrm{t}) \leq 1$; $0 \leq W_{P1}, W_{P2} \leq 1$; $\sum_{j=1}^{2} W_{Pj} = 1$; i=1, …, n.

Here, F_{Pi1}(t), the household i perceived the economic value of organic wine at time t, is a function of organic wine price, conventional wine price, and the willingness to pay a price premium for organic wine. F_{Pi2}(t), household i perceived the availability of organic wine at time t, is a function of the ratio of organic and non-organic wine bottles available in the shops stock. We assume that the proportion of organic to conventional wines is always equal in all shops. Therefore, the weight of price (W_{P1}) is considered to be 1 and the weight of availability (W_{P2})is set to 0. Equation 3.C2 indicates the household i perception of their ability to purchase wine at time t (F_{Pi}(t)) is bounded between 0 and 1. The sum of price and availability weights should be equal to 1.

Social Norm: Drinking wine with friends, family, or workgroups internalizes the social norms for wine consumption and preferences in individuals. Although researchers have already shown a strong relationship between socio-cultural norms and drinking behavior (Nwagu, Dibia & Odo 2017; Sudhinaraset, Wigglesworth & Takeuchi 2016), there are a few studies examining the influence of social pressures on purchasing organic wine (Thøgersen 2002). Social desirability can be an impetus for consumers' wine choice, especially when a wine is purchased for particular occasions or as a gift. In these situations, people often seek to satisfy social norms rather than personal preferences. Boncinelli et al. (2019) report that on gift-giving occasions, the probability of choosing organic wine is much higher than personal use. Researchers such as Johe & Bhullar (2016) emphasize that subjective appraisals of a reference group are a crucial predictor of organic wine purchasing intention. Here, we examine the impact of subject norms on buying organic wine.

F_{Si}(t), the household i subjective wine norm at time t, is calculated as:

$$F_{Si}(t)=\frac{F_{Spoi}\,(t)}{F_{Spi}(t)}\,; \qquad (3.C3)$$

where $0 \leq F_{Si}(t) \leq 1$; i=1, …, n;

F_{Spoi}(t) is the number of neighbors with organic wine preferences and F_{Spi}(t) is the total number of household i's contact network at time t. F_{Si}(t) higher than 0.5 represents organic wine as the norm while values less than 0.5 indicate that conventional wine is the perceived subjective norm. Equation 3.C3 determines which norm (i.e., organic or conventional) can guide a household decision to buy organic wine.

Intention: In TPB, factors including attitude, subjective norms, and perceived behavioral control shape the intention. An intention equal or higher than 0.5 refers to the preference for organic wine, while intention less than 0.5 refers to the preference for conventional wine.

F_{Ii}(t), the intention of household i for purchasing either organic or conventional wine is calculated as:

$$F_{Ii}(t)=\frac{(W_A F_{Ai}(t)+W_P F_{Pi}(t)+W_S F_{Si}(t))}{(W_A+W_P+W_S)}\;; \qquad (3.C4)$$

where $0 \leq F_I(t) \leq 1$; $0 \leq W_A, W_P, W_S \leq 1$; i= 1, ..., n.

Here, W_A the weight of attitude, W_P the weight of perceived behavioral control, and W_S the weight of subjective norms on intention are limited between 0 and 1. Equation 3.C4 assesses whether household i purchase to purchase organic wine, where an intention equal or higher than 0.5 is interpreted as organic wine purchase intention.

❖ Habit Formation

Habit concept has high relevance to wine purchasing behavior (Pomarici & Vecchio 2014; Vecchio 2013). For many years, habits have been evaluated through the past behavioral frequency of action in a stable context. Recently, researchers have criticized this method because it fails to explain whether a repeated action is deliberate or habitual (Lally & Gardner 2013). For example, a doctor may prescribe the same medicines to patients frequently, but it is not his habit. Thus, researchers have proposed atomicity, a complementary discourse to distinguish between habitual and non-habitual actions (Lally, Wardle & Gardner 2011). Habit formation follows an asymptotic curve, as a remarkable increase can be observed in behavior automaticity in the initial repetitions, and the automaticity growth rate gradually reduces until the behavior approaches its limit of automaticity (i.e., asymptote to be reached). In an experimental study about the impact of habit on promoting healthy eating and drinking behavior, Lally et al. (2010) found that for reaching up to 95% of the asymptote of atomicity, on average, 66 repetitions are required within a range between 18 to 254.

We assume that habitual purchasing behavior can be activated in all households. The behavioral rules for describing the habit formation in individual i is defined as in:

if (NE_i^o(t)> action repetition AND NE_i^c(t)< (0.3*NE_i^o(t))) (3.C5)

then (H_i^o (t)=uniform (0.7, 0.9, Randomness) AND H_i^c (t)=0); i= 1, ..., n.

Here, the number of times household i purchased organic (NE_i^o(t)) and conventional wines (NE_i^c(t)) up to time t are counted. If NE_i^o(t) is higher than the number of repetitions required to approach behavior automaticity (i.e., action repetition attribute in the model), and if NE_i^c(t) is smaller than 30% of NE_i^o(t), it is highly probable that household i purchases organic wine habitually at time t (presented as H_i^o(t)). The first condition of Equation 3.C5, on the one hand, satisfies that the number of times organic wine purchased by household i is sufficient to drive purchasing automaticity. The second condition, on the other hand, assures that the conventional wine purchasing of household i is occasional and does not interrupt the organic wine habit formation. If both conditions are met, then with a high probability household i purchases organic wine habitually at time t (H_i^o (t)). If the second condition changes to NE_i^c (t) between 30% and 50% of NE_i^o(t), then a weak habitual organic wine purchasing is considered for household i at time t. We apply similar logic for estimating the likelihood of habitual purchasing of conventional wine at time t (H_i^c(t)). Following, we explain how the goal frame is activated, and how does it interfere with habits if any.

❖ Goal-Frame

In the environmental psychology discipline, there are few articles examining the impact of conditional factors on decisions, systematically (Steg & Vlek 2009). Contextual factors such as price, availability, market forces, trust, grape variety, sales channel, and package can significantly influence organic wine purchasing behavior and mediate the relationship between intention and behavior (Ogbeide 2013a; Schäufele & Hamm 2017). The goal-framing theory assists us to analyze the mediating effect of context on wine preferences. We discuss this theory in Appendix 3.B.

In ORVin, three overarching goals, which are hedonic, gain and norm guide the wine choice of consumers. At any point in time, a combination of activated goals determines the perception and action of the individual. Personal interests, egoistic values, and enjoyment drive hedonic goals. Predicting the hedonism of households is difficult since measuring the emotions and pleasure is complex. It is not obvious what factors cause immediate pleasure and a sense of leisure in wine consumers. What we know so far is that when a person's decisions and actions are aligned with their intention, they have less internal disagreement (self-discrepancy), more satisfaction and self-fulfillment. Therefore, we assume that the value of hedonic goal for organic (FH_i^o(t)) and conventional wine (FH_i^c(t)) at time t are determined by either intention or habit depending on which one drives the behavior.

If the habit of household i is stronger than his/her intention at time t, then with a high probability, habitual behavior guides the behavior and considered as the value of hedonic goals. Moreover, if a strong habitual behavior exists, only under a stronger intention/motivation or interrupted purchasing pattern, this habit will be changed.

In the gain goal-frame, the individuals choose the most convenient or cheapest options available. For example, Vining & Ebreo (1992) showed that by changing contextual factors such as accessibility to recycling facilities, the individuals' gain goals become stronger. Minimizing expenditure is a popular objective for initiating gain goals for purchasing decisions. Here, we consider price as the main contextual factor influencing the wine preferences of households. By dividing the price of organic wine into the price of conventional wine and normalizing it, we estimate the organic gain goal of household i (FG_i^o (t)) and vice versa for conventional gain goal at time t (FG_i^c(t)). Changing the price of wines is well towards influencing the gain goals of consumers.

For modeling the effect of normative motive, we assess social dynamics based on individuals' observations at the wine shop. For example, observing neighbors sweeping the front door sidewalk increases the cleanness norms which eventually create a stronger normative goal (Steg, Lindenberg & Keizer 2016). In our model, household i observes the wine choice of other shoppers at the wine shop. This observation influences the wine norms of households and their purchasing decisions. F_{Sqoij}(t) and F_{Sqcij}(t) are the ratio of organic and conventional wine shoppers household i notices at shop j at time t. Household i organic ($FN_i^o(t)$) and conventional wine norm goals (FN_i^c(t)) at time t are considered as the average of perceived organic and conventional norms at the shop j and in the neighborhood at time t ($F_{Si}(t)$). Advertising campaigns and marketing guide the preference of consumers through affecting the normative goal of consumers.

A weighted aggregation of described elements is considered for determining how much household i values organic and conventional wine at time t as in:

$$GO_i(t) = \frac{(W_H FH_i^o(t) + W_G FG_i^o(t) + W_N FN_i^o(t))}{(W_H + W_G + W_N)} \quad (3.C6)$$

$$GC_i(t) = \frac{(W_H FH_i^c(t) + W_G FG_i^c(t) + W_N FN_i^c(t))}{(W_H + W_G + W_N)}$$

where $0 \le GO_i(t), GC_i(t) \le 1$; $0 \le FH_i^o(t), FH_i^c(t), FG_i^o(t), FG_i^c(t), FN_i^o(t), FN_i^c(t) \le 1$;

$0 \le W_H, W_G, W_N \le 1$; i= 1, ..., n.

Here, W_H, W_G, W_N denote the weight of hedonic, gain and norm goals, respectively. The values of all equation elements are bounded between 0 and 1. Equation 3.C6 determines the preference of household i at time t by considering organic and conventional wine pay off (GO_i(t) versus GC_i(t)). If the value of organic goal is bigger than the non-organic goals at time t (GO_i(t)≥GC_i(t)), then the household i prefers organic wine over conventional, and vice a versa. Table 3.C3 provides the complete set of rules used to define wine purchasing decisions.

Table 3.C3. Pay-off structure for consuming organic and conventional wine

Goals	If the planned decision of i is organic wine	If the planned decision of i is conventional wine
$\boldsymbol{FH_i^o}$**(t)**	If (intention organic i at time t >= habit organic i at time t), then, intention organic i at time t, else 1.	Intention organic i at time t.
$\boldsymbol{FH_i^c}$**(t)**	Intention conventional i at time t.	If (intention conventional i at time t >=habit conventional i at time t), then, intention conventional i at time t, else 1.
$\boldsymbol{FG_i^o}$**(t)**	1-[(price of organic wine perceived at time t-willingness to pay more) /(price of organic wine+price of conventional wine)].	1-[(price of organic wine perceived at time t - willingness to pay more) /(price of organic wine+price of conventional wine)].
$\boldsymbol{FG_i^c}$**(t)**	1-[(price of conventional wine perceived at time t) /(price of organic wine perceived at time t +price of conventional wine perceived at time t)].	1-[(price of conventional wine perceived at time t)/(price of organic wine perceived at time t +price of conventional wine perceived at time t)].
$\boldsymbol{FN_i^o}$**(t)**	An average of the number of organic shoppers at time t and F_{Si}(t).	An average of the number of organic shoppers at time t and F_{Si}(t).
$\boldsymbol{FN_i^c}$**(t)**	An average of the number of conventional shoppers at time t and F_{Si}(t).	An average of the number of conventional shoppers at time t and F_{Si}(t).

Appendix 3.D: Standard model tests

3.D.1. Sensitivity analysis

The values of parameters in the baseline setting influence the behavior and outcomes of the model. We derive settings for these parameters from either experimental data or calibration depending on the availability of data. For determining the parameter space of the model, we use One-Factor-At-a-Time (OFAT) method. In this method, we evaluate the impact of model parameters on the outputs by changing the value of one parameter at a time while setting the other parameters to default. Table 3.D1 presents the default value and the sensitivity range of key uncertain parameters. The key model parameters that we test for sensitivity are weight of attitude, weight of gain goals, weight of social norms, weight of hedonic goals, weight of PBC, and weight of normative goals. We test the sensitivity of key model parameters over their defined ranges to analyze the impact of uncertainty on the model behavior and facilitate the calibration process.

Table 3.D1. Model parameters tested in a sensitivity analysis

Parameter Description	**Default Value**	**Range for One-Factor-At-a-Time**
Weight of attitude on intention	0.55	0-1
Weight of PBC on intention	0.6	0-1
Weight of social norm on intention	0.16	0-1
Weight of hedonic goal on goal guided behavior	0.8	0-1
Weight of gain goal on goal guided behavior	0.4	0-1
Weight of normative goal on goal guided behavior	0.2	0-1

The results of sensitivity analysis for the listed parameters are shown in the following figures. The results are compared for different parameter settings after 100 weeks of simulation for 11 different stochastic realizations of the simulation for each setting. The main population shown in the model outputs is the population of organic wine consumers.

3.D.1.1. Attitude

The sensitivity analysis results for the weight of attitude on intention is illustrated in Fig 3.D1. This analysis indicates this parameter is less sensitive at values between 0 and

0.7. This means that the higher the influence of attitude, the more consumers purchase organic wine.

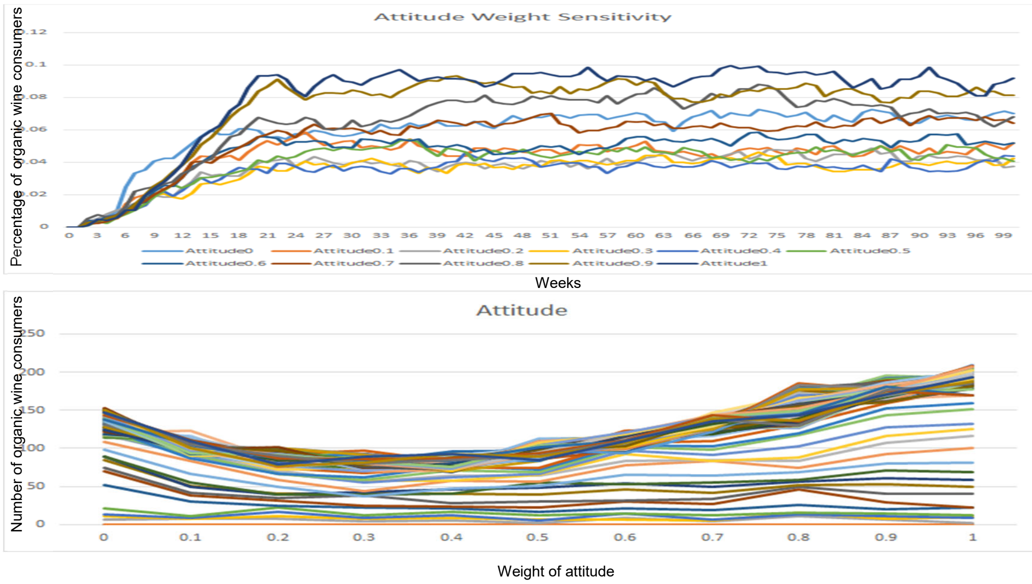

Figure 3.D1. The threshold value for weight of attitude on intention

3.D.1.2. PBC

Fig. 3.D2 presents the sensitivity analysis results for the weight of PBC on intention. This parameter has a high sensitivity to values less than 0.2. This means that the higher the price of organic wine, it becomes less likely to be purchased by consumers.

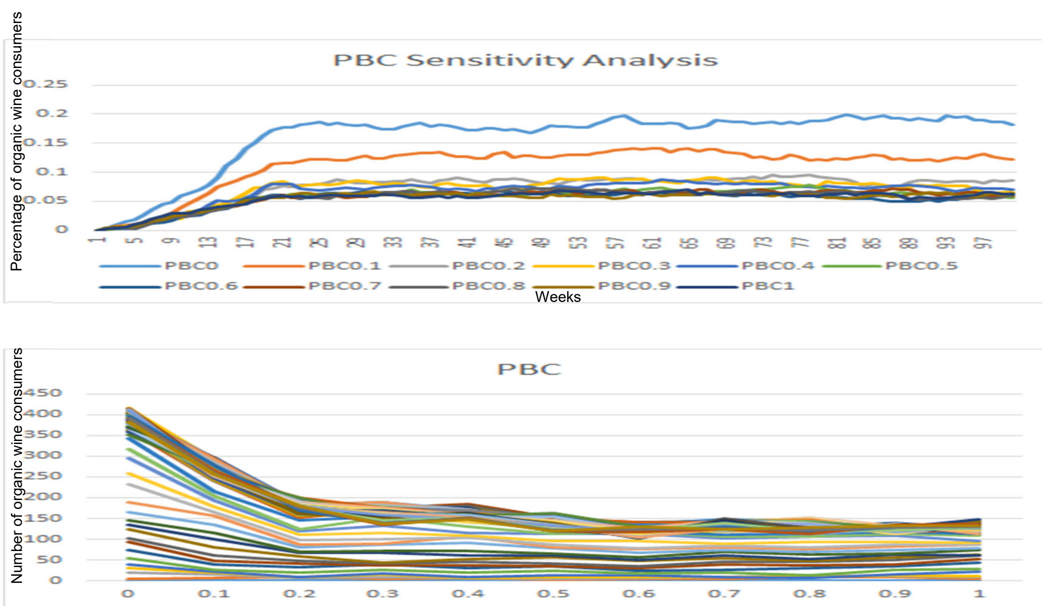

Figure 3.D2. The threshold value for weight of PBC on intention

3.D.1.3. Social norm

Figure 3.D3 presents the sensitivity analysis results for social norm effectiveness in influencing intention. This parameter in insensitive to values greater than 0.5. This means that the higher the weight of social norm on intention, the lower the number of households choose organic wine.

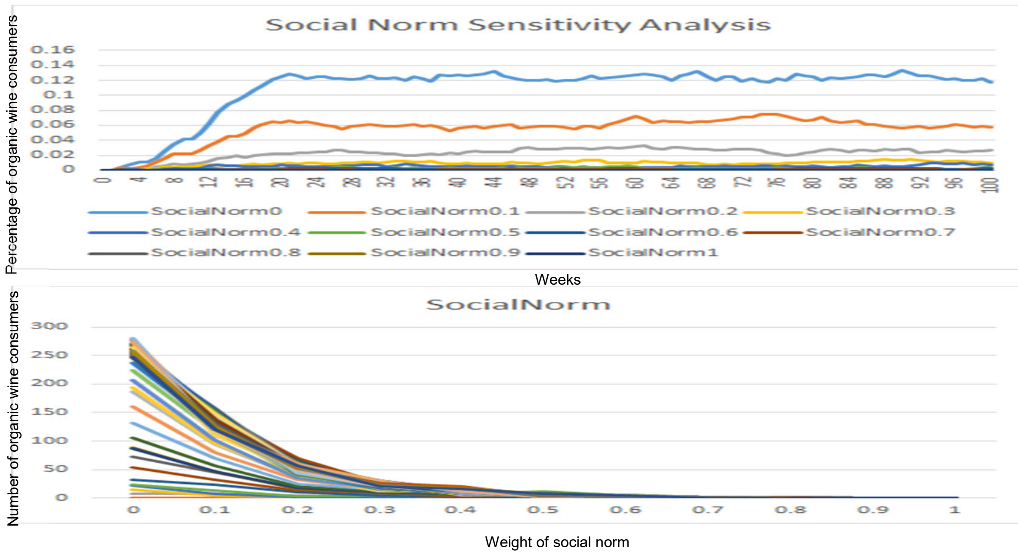

Figure 3.D3. The threshold value for weight of social norm on intention

3.D.1.4. Hedonic goal

Fig. 3.D4 presents the sensitivity analysis results for the probability that the hedonic goal guides the behavior. As it is shown, the number of people purchasing organic wine is insensitive to the value of smaller than 0.3 for this parameter.

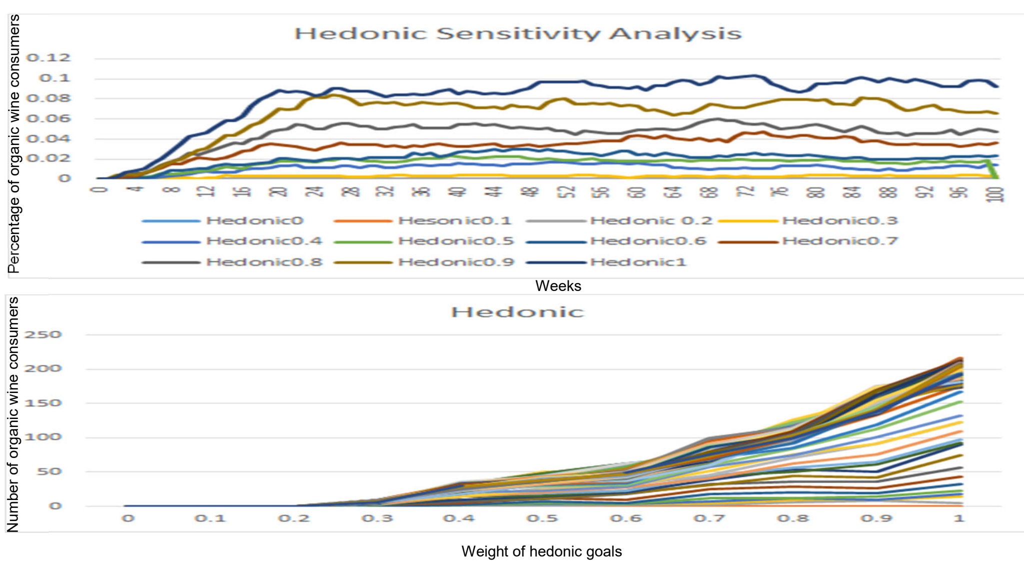

Figure 3.D4. The threshold value for weight of hedonic goals on goal guided behavior

3.D.1.5. Gain goal

Figure. 3.D5 presents the sensitivity analysis results for weight of gain goal on goal-guided behavior. This analysis indicates that setting a threshold value of 0.5 and greater for this parameter will minimize the sensitivity of outputs.

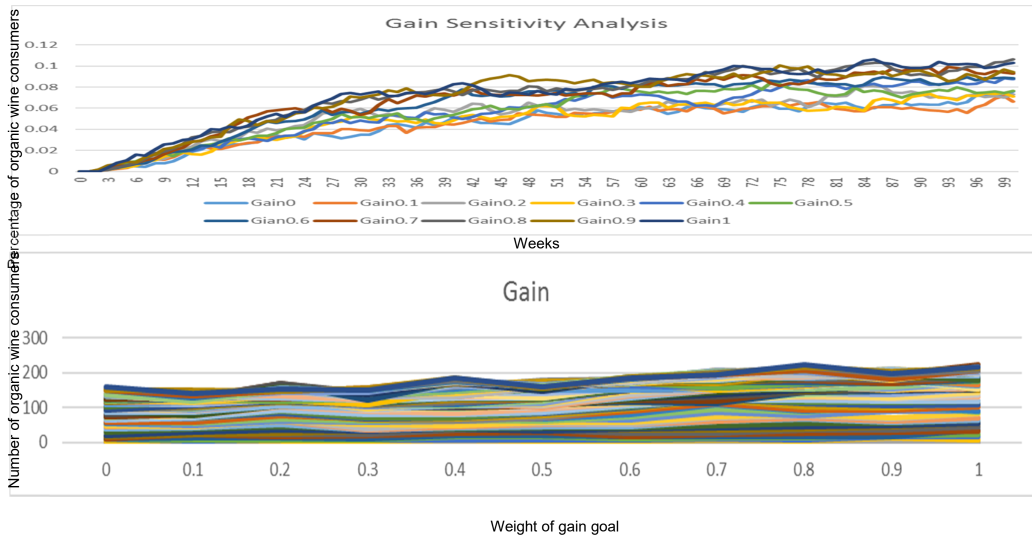

Figure 3.D5. The threshold value for weight of gain goal on goal guided behavior

3.D.1.6. Normative goal

Fig. 3.D6 presents the sensitivity analysis results of the threshold value of weight of normative goal on the goal-framed behavior. Here, the output of the model is insensitive to values greater than 0.4 while has the highest sensitivity between 0 and 0.1. It means that the higher the influence of other people at the shop on the wine choice of households, the lower the probability of purchasing organic wine.

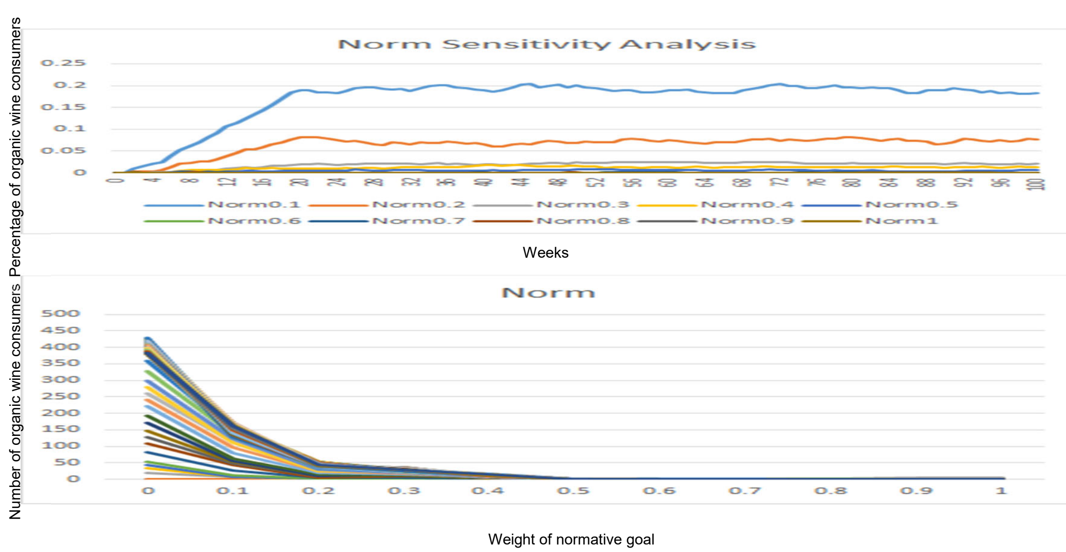

Figure 3.D6. The threshold value for weight of normative goal on goal guided behavior

3.D.1.7. Results

Table 3.D2 summarizes the direction and calculated correlation between uncertain parameters and the output. We can conclude that the weight of normative goals has the highest to the lowest influence on the output of the model. We refer to "lock-in situation" and "undercover altruism" phenomena to explain the influence of social norms on decision making in organic food context. This phenomenon explains that to integrate within a social group or avoid potential awkward social situations, individuals may choose to hide their virtuous, moral behavior in public. They tend to behave in the community's best interests rather than in their own best interest out of the fear or shame of a norm-deviating behavior, especially in ambiguous or uncertain situations. Thus, in the absence of social pressure, people may be more likely to choose organic wines. Similar results are obtained by Brouwer et al. (2017) and Scalco (2017), where consumers with high intention toward green products avoid purchasing them because they perceive their intention being against the norm.

Table 3.D2. Correlations between input and output variables

Input\Output	changes in the percentage of organic wine shoppers	Relationship direction
Weight of attitude	4%-10%	+
Weight of PBC	5%-20%	-
Weight of social norm	0%-13%	-
Weight of hedonic goal	0%-10%	+
Weight of gain goal	6%-10%	+
Weight of normative goal	0%-20%	-

3.D.2. Calibration

We calibrate the model by adjusting the most sensitive parameters to align the model results with available observed outcomes/data. In this regard, the weights of factors influencing attitudes such as health concerns, organic wine awareness, drinker type, and willingness to change are calibrated using the empirical attitude data reported by Ogbeide (2013a). Moreover, the weights of three intention components -- attitude, PBC, and social norms -- are calibrated against the available data for intention when the price of organic wines is 30% higher than conventional. The last set of parameters, the weights of goals (including gain, hedonic and normative goal), are calibrated with real market data about the percentage of organic wine consumers issued by experts in the Australian

Wine Institute (Wine Intelligence 2018). Table 3.D3 represents the list of parameters that we used for calibration and the values that delivered the best fit.

Table 3.D3. Calibrated parameters for the model

Calibrated parameters	Value	Calibrated parameter	Value
Weight of attitude	0.55	Weight of gain	0.4
Weight of social norm	0.16	Weight of hedonic	0.8
Weight of perceived behavioral control	0.6	Weight of social pressure	0.2
Weight of awareness	0.36	Weight of drinker type	0.34
Weight of health concern	0.3	Weight of willingness to change	0.05

Table 3.D4 shows the model calibration results. By changing the weights of attitude components, the value of calibrated attitude reaches 67%, only 1% higher than the experimental data. Moreover, the value of simulated intention is within the range of intention obtained from the experiment.

Table 3.D4. Calibration test results

Parameter	Data	Model outcome
Attitude	(Ogbeide 2013a)	
Positive	66%	67%
Willingness to pay	(Ogbeide 2013a)	
30% premium	21.15%-26.86%	24.86%
Wine purchase	(Lawson, Cosby, Baker, Shawn, et al. 2018; Wine Intelligence 2018)	
%Organic wine at 30% premium	7%-10%	7%-10%

3.D.3. Validation

For validation purposes, we used empirical data reported by Ogbeide (2013a). We estimate the intention of purchasing organic wine when the price of organic wines is 10%, 20%, and 40% (and more) higher than conventional wines and then compare the estimated results with the available data in the baseline scenario.

Table 3.D5 reports the validation test results. The simulation errors in all three cases (when the price of organic wine is 10%, 20%, and 40% more expensive) are small enough to be ignored. The validated model allows us to explore the consumers' wine preferences and test strategies that might be effective in changing their behavior.

Table 3.D5. Validation test results

Parameter	Data (Ogbeide 2013a)	Model outcome (Mean)
10% premium	56%-61%	56%
20% premium	42%-46%	42%
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Chapter 4:

Integrated Modeling of Extended Agro-Food Supply Chains: A Systems Approach

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Abstract

The current intense food production-consumption is one of the main sources of environmental pollution and contributes to anthropogenic greenhouse gas emissions. Organic farming is a potential way to reduce environmental impacts by excluding synthetic pesticides and fertilizers from the process. Despite ecological benefits, it is unlikely that conversion to organic can be financially viable for farmers, without additional support and incentives from consumers. This study models the interplay between consumer preferences and socio-environmental issues related to agriculture and food production. We operationalize the novel concept of extended agro-food supply chain and simulate adaptive behavior of farmers, food processors, retailers, and customers. Not only the operational factors (e.g., price, quantity, and lead time), but also the behavioral factors (e.g., attitude, perceived control, social norms, habits, and personal goals) of the food suppliers and consumers are considered in order to foster organic farming. We propose an integrated approach combining agent-based, discrete-event, and system dynamics modeling for a case of wine supply chain. Findings demonstrate the feasibility and superiority of the proposed model over the traditional sustainable supply chain models in incorporating the feedback between consumers and producers and analyzing management scenarios that can urge farmers to expand organic agriculture. Results further indicate that demand-side participation in transition pathways towards sustainable agriculture can become a time-consuming effort if not accompanied by the middle actors between consumers and farmers. In practice, our proposed model may serve as a decision-support tool to guide evidence-based policymaking in the food and agriculture sector.

4.1. Introduction

The dramatic growth of the world population and consumption has tripled demand for food over the past 50 years and led to increased pressure on the natural environment (FAO 2017). The contribution of agro-food production-consumption to eutrophication of surface water is estimated at 30% (Tukker & Jansen 2006). According to The Intergovernmental Panel on Climate Change (IPCC) (2019), this sector alone accounts for 25-30% of the total global anthropogenic greenhouse gas emissions. Despite irreversible impacts on environmental resources and biodiversity, a growing number of farmers adopt intensive agriculture methods. Primarily, they intend to minimize the production costs and inputs, maximize the yield of crops, achieve economies of scale, run their family business, and in some cases, raise mega industrialized farms. Recent studies show that not only the farmers and food suppliers but also distributors, retailers, and consumers are responsible for the environmental impact of global food systems (Notarnicola et al. 2017). Therefore, it is required to broaden the consideration of sustainability issues from an individual farm to the entire agro-food supply chain (SC).

The sustainable supply chain (SSC) concept has emerged as a result of incorporating environmental and social concerns into the economic management of production and distribution, from the point of origin to the point of consumption (Seuring & Müller 2008). Later, the concept of the circular supply chain (CSC) has been introduced to the field, which focuses on the after-consumption phase of products (Guide Jr & Van Wassenhove 2009). More recently, the concept of extended sustainable supply chains (ESSC) has been introduced, which goes beyond the pure operational view and accommodates the behavioral dynamics of production and consumption (further details can be found in Taghikhah, Voinov & Shukla (2019a)). The ESSC approach recognizes that sustainable consumer behavior is essential to drive the decision-making process along the whole SC for improving socio-environmental performance.

In this paper, we demonstrate an approach for modeling the ESSC and its operationalization. This study includes a multi-echelon supply chain network according to the ESSC framework in the context of the agro-food industry. It is composed of a set of farmers, processors, distributors, retailers, and customers; producing and consuming both organic and conventional food. We assess the SC performance in terms of economic, environmental, and social metrics. Our aim is to investigate the impact of shifts from conventional to organic food consumption on the underlying SC activities and behaviors.

In our literature survey, on the one hand, we found a few examples of SSC studies paying attention to the preference of consumers. For example, Fan, Lin & Zhu (2019) discuss the influence of the altruistic behavior of retailers on the willingness of consumers to purchase low-carbon products. They further study the effect of retailers' behavior across the entire SC to find out the dynamics of the economic and environmental performance of manufacturers. Tobé & Pankaew (2010) empirically study the influence of green practices of the SC on pro-environmental behavior of consumers. They conclude that a quarter of the Dutch population seems to be green consumers. Nevertheless, when it comes to buying decisions, the degree of environmental friendliness of products is not a significant determinant. Coskun et al. (2016) develop a model that considers the green expectations of consumers as a criterion for making decisions about the SC network configuration. They show the assets of the model in a hypothetical example where the consumers are categorized into the green, inconsistent, and red segments. Focusing on agro-food SC literature, Miranda-Ackerman, Azzaro-Pantel & Aguilar-Lasserre (2017) evaluate different pricing strategies based on consumer willingness to pay more for green food products. Sazvar, Rahmani & Govindan (2018) investigate the effect of substituting conventional product demand with organic assuming a percentage of consumers are willing to shift their preferences. Similarly, Rohmer, Gerdessen & Claassen (2019) show the impact of possible consumers' shift from meat-based to plant-based diet on the underlying production system.

On the other hand, there are studies from the economics and behavioral science discipline that consider some aspects of SCs. In the field of economics, for example, Wen, Xiao & Dastani (2020) and Sabbaghi, Behdad & Zhuang (2016) discuss the impact of consumer participation on pricing and collection rate decisions in CSC. The study of Safarzadeh & Rasti-Barzoki (2019) is another example of such analysis, which models the interactions between consumers, government, manufacturers, and energy suppliers for assessing residential energy-efficiency program. Regarding the behavioral studies, as a few examples, we point out to the impact of consumer choices on the retailing sector (He, Wang & Cheng 2013; Schenk, Löffler & Rauh 2007), energy market (Xiong et al. 2020), housing market (Walzberg et al. 2019), and so on. While researchers have taken initial steps in highlighting the role of consumers in managing SC operation, they are far behind in analyzing the behavior of various consumers and the collective impacts of changing their preferences on enhancing SC sustainability.

The main finding that can be drawn from the reviewed papers is that there is a lack of research that analytically considers the role of green consumer behavior in SCM.

Moreover, as there is no experimental or analytical study on the application of the ESSC framework, it still requires further investigations to be accomplished (Ferrari et al. 2019). According to Taghikhah, Voinov & Shukla (2019a), the complexity of relationships and the uncertainties involved in the ESSC requires a more comprehensive approach.

In developing the proposed ESSC model considering the heterogeneity of consumers, we take an integrated modeling approach combining agent-based modeling (ABM), discrete event simulation (DES), and system dynamics (SD) to simulate both production and consumption side of the operation and the feedbacks between them. ABM is a useful modeling approach for understanding the dynamics of complex adaptive systems with self-organizing properties (Railsback & Grimm 2019). It allows us to study emergent behaviors that may arise from the cumulative actions and interactions of heterogeneous agents. In the proposed model, we make use of ABM to define each supply chain echelon/actor as an agent with specific behavioral properties and scale. The dynamics of consumer behavior and buying patterns is also modeled using individual households as agents who decide what they buy. DES is used to define the behavior of farmer and processor agents (responsible for production and distribution) as a series of events occurring at given time intervals accounting for resources, capacities, and interaction rules. SD is employed in examining the behavioral patterns and interactions between farmers and market using aggregated variables. The decisions to be explored in the proposed model are related to land allocation, production planning, inventory control, pricing, and demand management under uncertainty. The model accounts for different temporal (from short-term to long-term decisions) scales and multiple objectives in supply chains. The applicability of the proposed model is illustrated in the particular case of the Australian wine industry. The rest of the paper is organized as follows: Section 4.2 presents a background on the wine SC characteristics and the modeling techniques applied in designing agro-food SC. Section 4.3 describes the model framework and method. Section 4.4 explains the details of a case study. Section 4.5 presents the calibration and validation results, the uncertainty analysis, and findings from the model. Finally, Section 4.6 derives conclusions and some practical and managerial perspectives.

4.2. Background

4.2.1. Sustainability considerations in agro-food supply chains

Farming, processing, distribution are the main functional areas of decision making in the agro-food SC. Strategic and operational farming decisions are about the time of planting and harvesting crops, the land allocation to each crop type, and the resources and agro-technologies to be used at the farm. Processing decisions refer to the scheduling of production equipment and labor, selecting production-packaging technologies, and controlling the inventory along the supply chain. The distribution related decisions involve designing the logistics network, scheduling the product shipping, and selecting the transportation modes and routes. The studies by Miranda-Ackerman, Azzaro-Pantel & Aguilar-Lasserre (2017), and Jonkman, Barbosa-Póvoa & Bloemhof (2019) are recent examples of models addressing a range of decisions from farm level (e.g., organic versus conventional farming) to the production (e.g., technology selection) and distribution level (e.g., transportation route). Although studies addressing SC decisions simultaneously are still lacking, the literature trend is towards more integrative, holistic agro-food models.

Strategies aimed at reducing the environmental footprints of agro-food SC are mainly focusing on the production side, designing low-carbon logistics networks, and improving the resiliency and reliability of food delivery (Soysal et al. 2012). These improvements alone may not bring considerable emission savings to agro-food sector. For example, in the case of meat production, which is responsible for approximately 14.5% of total global GHG emissions (e.g., Mohammed & Wang (2017)), even more than the transportation sector (Gerber et al. 2013), introducing green logistics and optimizing energy consumption in the SC will hardly make a significant difference in its overall impact. Regarding the food miles and local sourcing, new studies show that imported food products do not necessarily have higher environmental impacts than locals (Nemecek et al. 2016). Using eco-friendly processing technologies (Aganovic et al. 2017) and utilizing novel packaging options (Licciardello 2017) are examples of efforts to reduce the environmental footprint of food processing. An insightful discussion on these strategies can be found in Li et al. (2014). Among the strategies examined in the literature (Beske, Land & Seuring 2014), demand-side solutions such as consumer preferences for sustainable food or vegetarian diets and their influence on the overall configuration and performance of the SC have been largely ignored.

For the production-side strategies, we focus on expanding organic food production systems. With regard to the environmental burdens of organic farming, scholars have arrived at contradictory recommendations. In the first set of studies, they have proposed organic farming system as a promising environmental solution due to a significant reduction in agricultural inputs resulted from enhanced soil organic matter and thus soil fertility (Markuszewska & Kubacka 2017). In another set of research, organic farming is not positively assessed, and the studies have also questioned as to what extent it can improve environmental performance. At the same time, more lands are required to produce the same amount of yields (Tuomisto et al. 2012a). The contradiction between the results of the assessment is due to the limitations of LCA (van der Werf, Knudsen & Cederberg 2020). Researchers advise that although there is no single best farming system, in many circumstances (depending on soil type, climate, altitude, and legislation), organic farming can be considered as the optimal system creating more resiliency in food systems. For a comprehensive discussion around the topic of organic versus conventional farming, we refer interested readers to Risku-Norja & Mikkola (2009).

4.2.2. Modeling methods in the agro-food supply chain

From a modeling perspective, mathematical optimization techniques (combined with life cycle assessment) are the dominant approach used for designing SSC for food products (Zhu et al. 2018). Some researchers take deterministic approaches such as linear programming, mixed integer programming, and goal programming (Oglethorpe 2010) to design and plan SCs. The uncertainty and dynamics in the parameters are addressed by approaches such as stochastic programming (Costa, dos Santos, et al. 2014), fuzzy programming, simulation modeling, and game theory. The choice of modeling technique depends on various factors such as problem scope, inherent complexity, and uncertainty in the SC, modelers' skill, and data availability.

Although a decade ago, the increasing necessity of using system science methods, such as ABM, SD, and network theory for studying agro-food SCs have been emphasized (Higgins et al. 2010), not many applications can be found in practice. Authors have applied ABM in developing theories and policies to improve the performance of the agro-food industry (Huber et al. 2018). Theory focused studies aim to explore the application of theories in understanding agents decision-making process (e.g., farmer, government, dealer, etc.) or develop new theories to explain the interactions among individual agents (e.g., Malawska & Topping (2018)). Theories have already helped to describe the formation of cooperation networks, restructuring the partnerships, and rearrangement of the market power (See Utomo, Onggo & Eldridge (2018)). Policy focused ABMs study the impact of financial (e.g., incentives and subsidies, pricing, credit, and compensation schemes), innovative and technological (e.g., improved seed, tree crop innovations, or environmental (e.g., organic agriculture, organic fertilizers) policies on the performance of food SC (Albino, Fraccascia & Giannoccaro 2016). In a recent review on the application of ABM in agriculture, Utomo, Onggo & Eldridge (2018) emphasize that important actors of the industry, such as food processors, retailers, and consumers, are rarely modeled in the current ABM literature and call for further research on these areas.

Despite the growing interest in using optimization approaches, the application of simulation techniques in the SSC context is scarce. Recently, Wang & Gunasekaran (2017), Rebs, Brandenburg & Seuring (2018), and Brailsford et al. (2019) have suggested getting the advantages of combined simulation modeling methods in assessing complex SSC problems. In response to this call, our study presents the development of an extended food SC model that incorporates the dynamics of farmers, processors, retailers, and consumers behavior as well as sustainability aspects. For this we used an integrated, or rather an integral (Voinov & Shugart 2013) modeling approach to link production decisions to consumption choices in a holistic way.

4.2.3 Behavioral modeling and hybrid simulation

In recent years, the area of modeling behavioral aspects of decision-making has received the attention of researchers and practitioners. The behavioral modeling approach presents an alternative basis for decision making in supply chains, which are traditionally modeled largely with mathematical optimization models. In behavioral models, individual decisions are modeled as per the definition of bounded rationality where decisions are made with respect to the limited available information, individual preferences and biases, cognitive limits, and time available to make decisions. For example, Kunc (2016), provided a useful resource to understand the use of system dynamics based simulations for behavioral modeling. These types of modeling approaches can provide new and emergent insights about operations and supply chain management. However, the use of behavioral modeling methods should be carefully designed and validated as such approaches can also introduce undesired complexity, higher ambiguity in the modeling environment, and harder interpretation of results. For a comprehensive discussion on this topic, see Kunc, Malpass & White (2016).

Commonly used methods for quantitative analysis in supply chain management, largely, relied on the optimization approaches based on constrained linear and nonlinear optimization algorithms, as well as dynamic programming and discrete optimization exact methods, heuristics and metaheuristics (Barbosa-Póvoa, da Silva & Carvalho 2018). While these approaches performed well generally, but they fall short in modeling behavioral aspects that are bounded rational in nature. Methods such as SD, ABM are able to simulate the intangible aspects of the SCM effectively, including interactions among different SC stages, learning over time for SC partners involved, and continuous feedback on key decisions in the presence of limited information. However, studies employing simulation modeling (e.g., ABM, SD) in the area have been few and far between, as reported in the recent study by Dharmapriya, Kiridena & Shukla (2019). In fact, there are even less studies reported on modeling consumer behaviors in the SC using simulation modeling (Taghikhah, Voinov & Shukla 2019a).

Hybrid simulation is an approach that involves integrating multiple simulation methods such as DES, ABM, and SD (a comprehensive taxonomy can be found in Mustafee & Powell (2018)). It has a strong practical appeal to deal with the limitations of a single method in developing behavioral modeling (Mustafee et al. 2017). This approach allows the models with different levels of abstractions to interact with each other and increases the flexibility of end-users in using them for decision-making. The main challenges of hybrid simulation are difficulty in verification and validation, huge computational complexity (Bardini et al. 2017), and low practical applicability for solving real-world cases. Brailsford et al. (2019) found that among 139 published papers using hybrid simulation, combined SD-DES is the most popular method. In contrast, a combination of DES, SD, and ABM is the least used method, reported only in 14 papers. In this paper, we compared the results of using both approaches and provide insight into their performance in a case study. For in-depth analysis of hybrid modeling, see Brailsford et al. (2019), Eldabi et al. (2018), and Mustafee et al. (2017).

4.3. Methodology

In this study, SC is composed of four actors/echelons - farmer, winemaker, retailer, and consumer - collaborating to achieve their various goals (see Figure 4.1). They may have different functions, complexity levels, temporal dimensions, and spatial scales. In the proposed ESSC model, ABM is used together with DES and SD to model the behavior of each actor. The model is programmed in AnyLogic 8.3 Software and it is openly available at Comses (https://www.comses.net/codebase-release/eeb3cd12-91ac-4ba7-81f7-8c8bfe7bd804/). It is built in a GIS computational environment enabling users to adjust the resolution and scales during the run time.

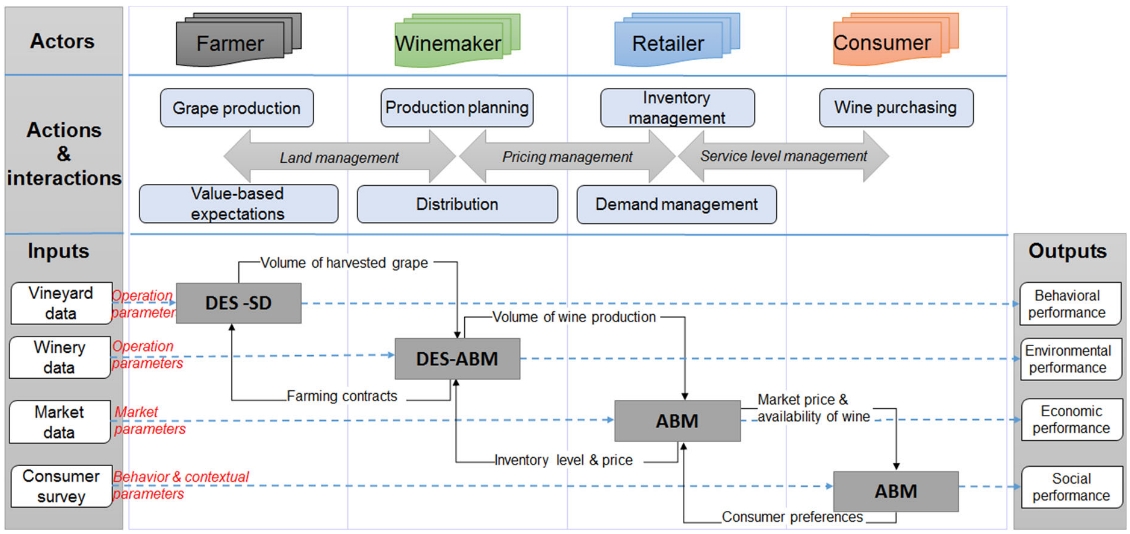

Figure 4.1. Conceptual framework of ESSC for the wine industry

The wine market studies reveal that retailers have high bargaining power (Australian competition and consumer commission 2019a). Recently, concentration in most of the retail industries including liquor has increased, with only a few retailers controlling the large market share and setting the prices and quantities strategically. The oligopolistic behavior of retailers significantly reduces winemakers' power in their negotiations and turns them into price takers.

Having said that, winemakers still have a significantly stronger bargaining position compared to grape growers. In other words, farmers cannot merely pass higher grape prices and other costs along the supply chain to wineries. These considerations justify the assumptions of hierarchical structures and central control changes to collaboration between actors to maximize the profit.

4.3.1. ESSC inputs

Both historical and empirical data are used to parameterize, calibrate, and validate the model (for more details refer to sections 4 and 5 and appendix B, C, and D). The data on crop scheduling, vineyard costs, farming practices, grape types, and land yield describe the farmer agents. The winemaker agents use historical data on numbers and capacities of machinery, production processes, time, costs, and grape requirements. The information collected from liquor retailers' annual reports and the wine industry reports, including the prices, market structure, export and import, sales, and profit of retailing, addresses the data inquiry of retailer agents. Finally, consumer surveys about wine preferences provide data for the behavioral (e.g., beliefs, goals, experiences, and perceptions) and contextual factors (e.g., price, availability, accessibility) of the consumer agents. Regarding the intermediate link, as shown in Figure 4.1, the consumer preferences and demand for products (derived from consumer ABM) influence the retailers selling price and availability of wine types (derived from retailer ABM). This price and availability dynamics in conjunction with the volume of wine production (derived from winemaker DES-ABM) affect the wine inventory levels, order size, and retailers purchasing prices. These changes in the volume and price of wine are reflected in farming contracts and determine the volume of grape harvest (derived from farmer DES-SD).

4.3.2. ESSC methods

An integrated ABM-DES-SD method is employed for the ESSC model development. We use ABM for simulating consumer behavior and retailer operation. It is a bottom-up method suitable for modeling complex social, behavioral dynamics to study heterogeneity and the emergence of collective actions. In facing the same situation, every consumer and retailer agent has a unique reasoning mechanism, and they act based on predefined decision rules. A combination of DES and ABM is employed for modeling the dynamics of wine production and distribution operations. DES presents (discrete) sequence of wine processing events in time. Finally, a combined DES and SD method simulates the annual growth cycle of grapevines and predicts farmers' expectations about the value of organic farming (Figure 4.1).

4.3.3. Actions and behavior of agents

4.3.3.1. Farmer agent

Farmers act as the first-tier suppliers in the model. They grow two types of grapes - organic and conventional, which are harvested once a year. Depending on the availability of arable land and the farming practice (organic versus conventional), each farmer agent has a distinct production capacity and unit operating cost. Figure 4.2 presents a simplified schematic of farmer operations.

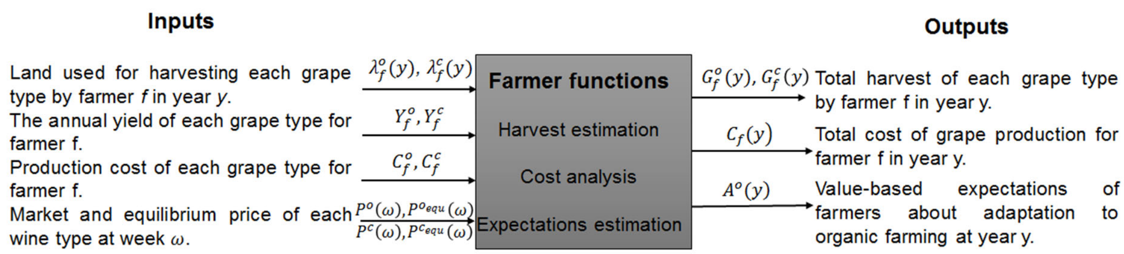

Figure 4.2. Schematic of operations in farmer agents

The model assumes that farmers have fixed land area available to supply the grape requirements of wineries. Farmers are contracted by winemakers to grow grapes under a capacity guarantee contract-farming scheme. This contact determines the approximate volume and the type of grapes - organic and conventional - required for production. In this study, organic farming refers to a method of crop production that relies on biological pest controls (e.g., cover crops), and organic fertilizers (e.g., manure). Conventional farming, in contrast, uses synthetic fertilizers, fungicides, and pesticides to maximize the vineyard yield. The organic farming system is considered more sustainable since it can keep soil healthy and maintain the productivity of land. The simulation begins in springtime when the grapevines are in the bud break phase. In this phase, tiny buds start to swell and eventually shoots grow from the buds. Approximately 40-80 days later, small flower clusters appear on the shoot, and the flowering phase starts. Soon after, 30 days on average, the flowers are pollinated, and the berries start to develop. This crop phase determines the potential yield of the vineyard. In the next phase, veraison, the color of grape berries changes after 40–50 days signaling the beginning of the ripening process. Following veraison, within 30 days, farmers complete the harvest, remove grapes from the vine, and transport them to wineries for further processing. Due to the variation in climate conditions over the years, we consider a stochastic crop growth process where the annual harvest of organic and conventional grapes is:

$$G_f^o(y), G_f^c(y) = \{\lambda_f^o(y)Y_f^o, \lambda_f^c(y)Y_f^c\}; \quad (4.1)$$

Where, $\lambda_f^o(y), \lambda_f^c(y)$ are grape yields and Y_f^o, Y_f^c are cultivated areas at year y for organic and conventional grapes at farm *f*. The annual production cost at farm *f* ($C_f(y)$) varies depending on the production cost of organic and conventional grapes.

Farmer agents make judgmental assessments of the value of organic and conventional farming systems. The hypothesis of adaptive expectations (Nerlove 1958) states that the expectations of the future value of the interest variable depends on its past value and adjusts for the prediction error. Thus, the calculation of progressive expectations or error learning hypothesis is derived from observing the difference between past and present market values. The market and equilibrium price of organic and conventional wine (discussed in Section 4.3.4) guide farmers' expectations of adaptation to organic farming (shown in Figure 4.3).

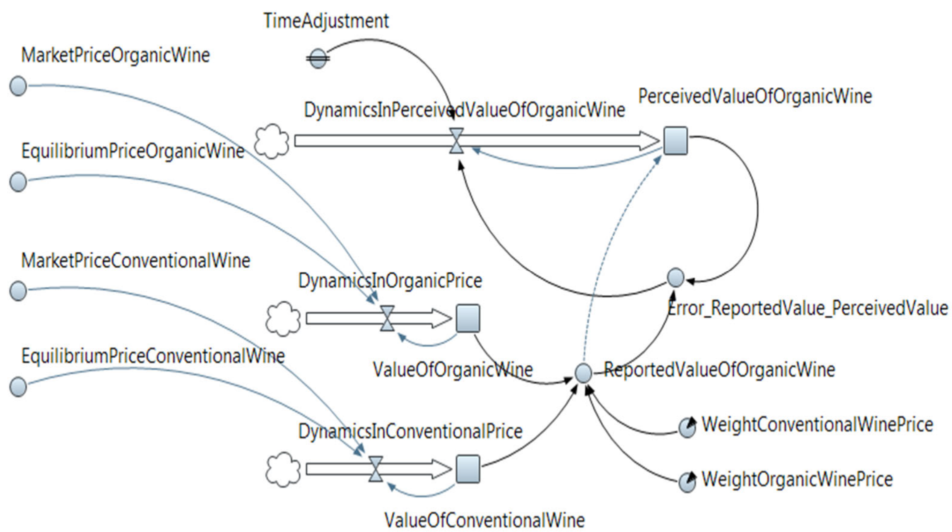

Figure 4.3. Value-based expectations of farmers about organic farming

The current expectations of the value of organic farming in the future is calculated as:

$$A_f^o(y) = \int_0^{\omega} \varphi_f^{o_{out}}(\omega) d\omega; \qquad (4.2)$$

$$\varphi^{\,o_{out}}(\omega) = \begin{cases} 0, & if\ (\varphi_f^{o_{out}}(\omega) \leq\ 0\ and\ \varphi_f^{o_{err}}(\omega)/t < 0)\ or\ if\ (\varphi_f^{o_{out}}(\omega) \geq 1\ and\ \varphi_f^{o_{err}}(\omega)/t\ > 0); \\ \varphi_f^{o_{err}}(\omega)/t, & else; \end{cases}$$

$$\varphi_f^{o_{err}}(\omega) = \varphi_f^{o_{in}}(\omega) - \varphi_f^{o_{out}}(\omega);$$

Where $\varphi_f^{o_{out}}(\omega)$is the past perceived value of organic wine, $\varphi_f^{o_{err}}(\omega)$is the partial adjustment, which describes the gap between reported value $(\varphi_f^{o_{in}}(\omega))$ and the perceived value of organic wine. A full description of sub-models and their equations is available in Appendix 4.A.1.1.

4.3.3.2. Winemaker agent

Winemaker agents process grapes to produce two types of products, organic and conventional wines. They are responsible for storing and dispatching final products to retailer agents. The total production capacity per agent is fixed, but periodically, the capacity ratio for organic and conventional wine production can adapt to the size of retailer orders. Figure 4.4 presents the operations in winemaker agents.

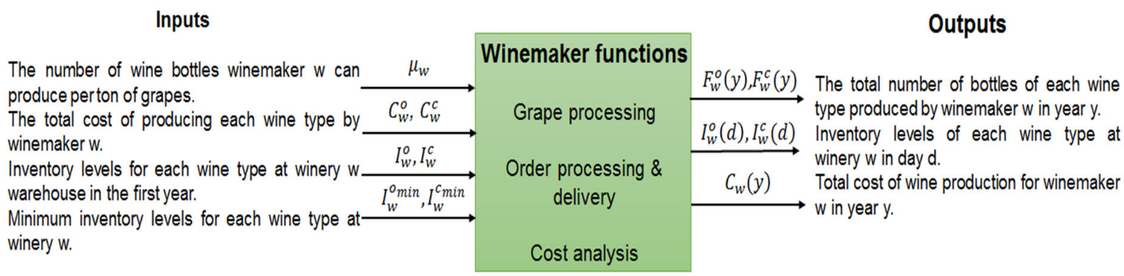

Figure 4.4. Schematic of functions in winemaker agents

Due to perishability issues, winemakers try to process the grapes straight away after the harvest. The grapes get sorted, crushed and pressed, fermented, matured, and bottled as organic and conventional wines. Assuming winery *w* purchases all the farmer *f* yield, their annual production is:

$$F_W^o(y), F_W^c(y) = \{G_f^o(y)\mu_W, G_f^c(y)\mu_W\}; \qquad (4.3)$$

Where $G_f^o(y)$and $G_f^o(y)$ are the availability of raw materials from (1) and μ_w is the capacity of processing facilities. While the same type of machinery can be used for producing organic and conventional wines, the processes (e.g., excluding sulfate during fermentation and bottling for organic wine) and associated costs might be slightly different. Upon order arrival from retailers, the winemakers check for the stock availability and follow a rule-based reasoning approach to best fulfill them as described in Appendix 4.A.1.2.

To prevent the issuance of new orders in case of no stock, winery *w* informs all the retailer agents that due to unavailability of stock $\{(I_W^o(d),\ I_W^c(d)) < (I_W^{o_{min}},\ I_W^{c_{min}})\}$, they would not accept further orders. This is done because wine production can take place once a year at the end of harvest season. Before this time, any new order will be placed in the queue for processing when the product is available.

4.3.3.3. Retailer agent

Retailer agents have the responsibility of supplying products quickly and reliably, forecasting demand accurately, and controlling the inventory levels continuously. They employ dynamic inventory control models to make a trade-off between SC costs and demand fulfilment. Figure 4.5 summarises the operations in this agent type.

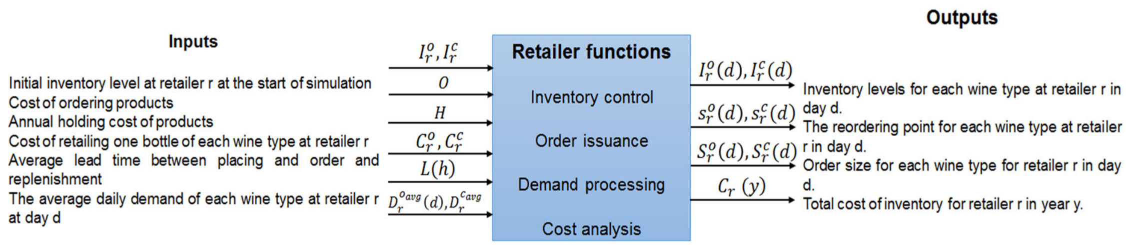

Figure 4.5. Schematic of operations in retailer agents

The decisions on when to place an order and how many products to order from winemakers can impact the inventory-related costs. A continuous review inventory policy meets the requirements of retailers in response to dynamic demand situations (Hollier, Makj & Lam 1995). This policy allows them to review their inventory levels for both organic and conventional products on a daily basis at minimum costs. When the inventory drops to some predetermined level '*s*' (known as reordering point), lot of size '*S*' is ordered. The reordering point ($s_r^o(d)$,$s_r^c(d)$) makes sure that sufficient stocks are available to meet the demand before the order arrives at the retailer *r* to replenish the inventory levels. The order size for retailer *r*, ($S_r^o(d)$, $S_r^c(d)$) is a function of the economic order quantity ($Q_r^o(d)$, $Q_r^c(d)$) and the inventory at hand ($I_r^o(d)$,$I_r^c(d)$). Appendix 4.A.1.3 presents the details of inventory management system.

4.3.3.4. Consumer agent

Consumer agents follow a certain decision-making process to make choices between organic and conventional wines. ORVin, an ABM developed by Taghikhah et al. (2020), is integrated into our model to estimate the consumer preferences for wine. In exploring the cumulative market consequences of individual consumer choices, factors such as social influence, drinking habits, and behavioral dynamics come into play. Figure 4.6 presents a summary of the functions used in this agent type.

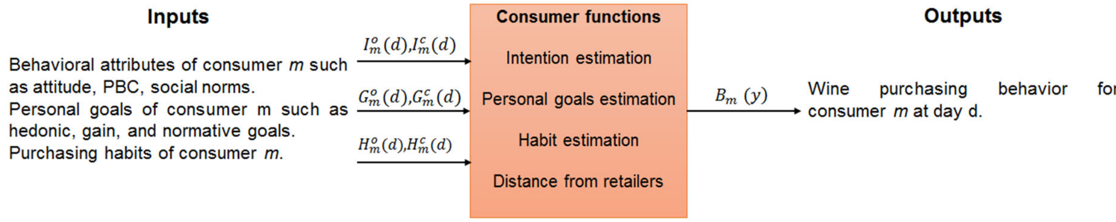

Figure 4.6. Schematic of functions in retailer agents

To understand the wine purchasing behavior, the theory of planned behavior (TPB) (Ajzen 1985) is considered along with alphabet theory (Zepeda & Deal 2009) and goal framing theory (Lindenberg & Steg 2007). According to TPB, a particular behavioral choice is preceded by intention, which in turn is influenced by an individual's behavioral attitudes, normative beliefs (i.e., social influence, perception of social pressures, belief that an important person or group of people will approve and support a particular behavior), and control beliefs (belief in ability to influence own behavior, and control behavioral changes resulting from specific choice). However, Alphabet theory explains the influence of habits on the relationship between intentions and actual behavior (e.g., organic food purchase). Besides habits, the goal-framing focuses on the impact of enviro-contextual conditions on personal goals (i.e., hedonic-gain-normative goals) when making decisions. In this study, we have included all of these theories in an integrated framework setting for exploring behavioral and contextual factors, including intentions, habits, and personal goals that may influence wine purchasing decisions. This combination provides a theoretical framework for exploring behavioral and contextual factors, including intentions, habits, and personal goals that may influence wine purchasing decisions. Consumers have intentions for purchasing either organic or conventional wine before shopping. When they arrive at the nearest retailer, they first check the availability and price of wine types. If the price of wine is higher than the consumers' spending limit or if no wines are available in stock, they leave the shop without purchasing any wine. Otherwise, they choose wines based on their intentions, habits, observations of what other shoppers buy, and the perceived value of products. During the simulation, the shopping experience, the information about organic wine, and the dynamics of price and availability of wines affect the wine preference of consumers. For a technical explanation of the model, please refer to Appendix 4.C: ORVin model description in (Taghikhah, Voinov, et al. 2020a).

When integrating ORVin into the ESSC model, some restrictions of the model could be released as below.

- In ORVin all the retailers have equal stocks of wine. Now, retailers are different, and, apart from price considerations, the product availability on the shelf can affect the perception of consumers about their choice control (i.e., perceived behavioral control (PBC)).

- In ORVin no product shortage is allowed, and the service level is 100%. Now some acceptable level of product shortages can happen, and these are modeled as a service level.

4.3.4. Agent interactions specification

Figure 4.7 displays the interactions of agents supporting the operations of ESSC. Three interaction schemes are proposed: service level management scheme, pricing management scheme, and land management scheme.

Retailer agents are gatekeepers between the producer and consumers. In interactions with consumer agents, retailer agents have multiple touchpoints to influence consumer preferences, including prices, and on-shelf availability. There are situations when wines of a certain type, for example, conventional ones, are not available at the shops. If consumer *m* habit of purchasing conventional wine is weaker than their intention to purchase organic wine ($H_m^c(d) < I_m^o(d)$), a shift in their preference (from conventional to organic wine) can occur that may lead to purchasing organic wine (also depending on the other factors). A detailed description of the interactions between consumer and retailer agent is in Appendix 4.A.2.1.

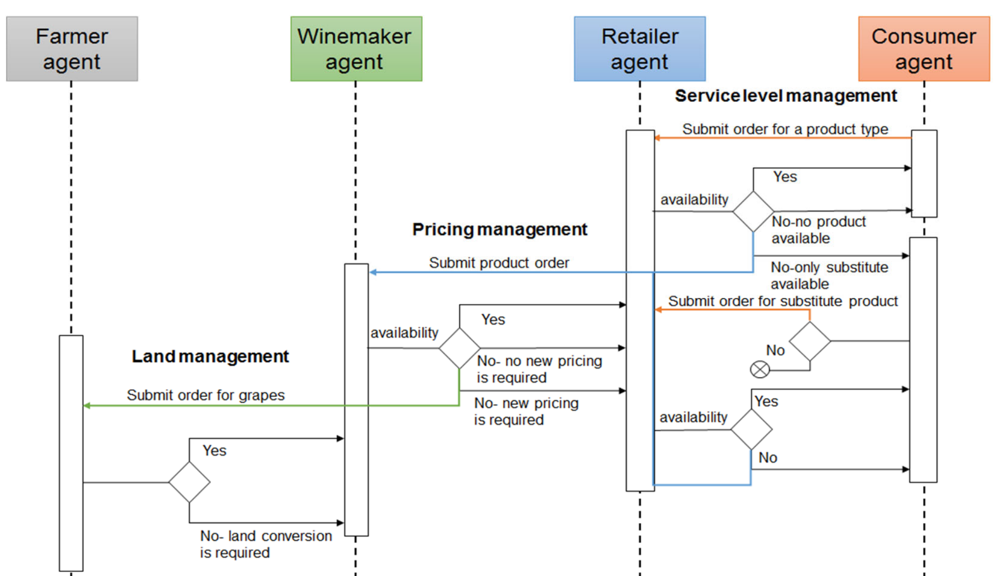

Figure 4.7. ESSC interactions schemes

Retailers are also responsive to the changes in the demand for products to keep the profit margin of SC stable. For maintaining high service levels (i.e., acceptable stockout rates), they may adjust inventory policies and set new pricing strategies. They should keep the inventory stock-out at an acceptable level to timely meet customer demand.

The service level at week ω is:

$$\vartheta_{\%}(\omega) = 1 - (N_m^{l_{avg}}(\omega)/N_m^T); \qquad (4.4)$$

Where $N_m^{l_{avg}}(\omega)$ is the average number of lost consumers and N_m^T denotes the total population of households. $\vartheta_{\%}(\omega)$ should not drop to less than the minimum acceptable level (assumed to be 95% (ϑ=0.95)).

In transitioning demand from one product type to another, for instance, from conventional to organic wine, the conventional wine stock level grows, and at the same time, the organic wine stock level declines in the SC. This supply-demand imbalance prompts retailer-winemakers interactions, where they take different pricing strategies. Retailer agents monitor the dynamics in the organic and conventional wine inventory stocks using statistical process control (SPC) charts (Oakland 2007). Upper and lower control limits for the wine inventory SPC charts are yearly determined following a set of production rules, as presented in Appendix 4.A.2.3. Nelson rule checks whether the process is in control/out of control.

According to Nelson rule 8, if the inventory level is out of the defined upper and lower limits for at least nine consecutive time units, then the process is uncontrolled. For example, in situations when due to the changes in the market trend, there is a shortage of products, the prices are subjected to rise to rebalance the demand and supply. Generally, oversupply leads to a drop in the market prices while undersupply increases the market prices of organic and conventional wines ($P^o(\omega), P^c(\omega)$) by a predetermined rate (R^o, R^c). The changes in the market price of wines cannot drop below the minimum ($P^{o_{min}}, P^{c_{min}}$) or go beyond the maximum price of wines ($P^{o_{max}}, P^{c_{max}}$). As the price of products will change temporarily over a short period, it may not be effective in coping with the market price gap when there are significant supply and demand imbalance. Price adjustment is an effective market mechanism aiming to tune the equilibrium prices ($P^{o_{eqb}}(\omega), P^{c_{eqb}}(\omega)$) for increasing or decreasing the sales of a product for longer periods. Instead of a fixed price option, wine equilibrium prices are modified on a γ week-by-week basis at different rates except during the land conversion period from conventional to organic.

A sequence of decisions winemakers and retailers make about the wine prices affects the production plans and supply agreements with farmers. When the profit from a certain wine type increases, its production becomes financially more attractive and viable to winemakers. In these situations, the winemakers send revised orders to farmers requesting for different quantities of each grape type and proposing a new price schedule for the yields. Farmers respond to these requests by evaluating their capabilities in terms of whether they can fulfill the order with the current vineyard configuration, or they need to convert a portion of their farmland to organic/conventional to meet the future demand from the winemakers. Appendix 4.A.2.3 provides a detailed explanation of the farmers' capacity and decisions about fulfilling the winemakers' orders for grape.

Thus, both parties decide on the volume and selling price of yield in a renewed contract farming agreement as summarized below.

Convert from conventional to organic farming: No changes in the production plan and vineyard configuration is expected unless the equilibrium price of organic wine increases before the planting season ($\Delta P^o(y)$>0). The organic conversion scale (the amount of land to be converted in year y) is:

$$\Omega^o(y) = \begin{cases} \max\{\Omega^{min}, \chi^o(y)\}, & \text{if } (\delta^o(y) \leq 0.3); \\ \Omega^{min}, & \text{if } (0.3 < \delta^o(y) \leq 0.7); \\ \min\{\Omega^{min}, \chi^o(y)\}, & \text{if } (0.7 < \delta^o(y)); \end{cases} \quad (4.5)$$

Here, Ω^{min} is the minimum conversion scale, $\chi^o(y)$ is the land required for conversion based on demand estimations, and $\delta^o(t)$ is the perceived failure risk of conversion. The transition from conventional to organic farming takes three years. The yield from transitioning farms can be only sold as conventional products. This long lead time not only adds to the complications of balancing market demand but also gives a bias to farmer judgments about the long-term cost-benefits of their organic vineyards as discussed in Section 4.3.3.1.

Revert from organic to conventional farming: The decisions on increasing the production volume of conventional wine and reverting from organic to conventional agriculture impose higher risks on the financial performance of SC. In this model, the dynamics of equilibrium price of organic and conventional play the main role in provoking the reversion decisions ($\Omega^c(y) = \Omega^{min}$) as:

- If there is no positive change in organic wine equilibrium price while the conventional equilibrium price is increasing and the SC service level is less than the minimum acceptable level, or
- If there is an oversupply of organic wine and its equilibrium price is at a minimum.

4.3.5. ESSC outputs

Sustainability objectives, including social, environmental, and economic considerations as well as behavioral considerations, guide the ESSC decisions.

We address the social issues from the public health perspective as a function of organic food consumption. Organic diets expose consumers to fewer chemicals associated with human diseases such as cancer (Chen et al. 2015), autism (Kalkbrenner, Schmidt & Penlesky 2014), and infertility (Chiu et al. 2018). Kesse-Guyot et al. (2017) reported that the risk of obesity in organic food consumers is reduced by 31% as a result of adopting a nutritionally healthier dietary pattern. It could also be noted that the people making organic food choices are usually more informed about their diet and lifestyle choices, which could, in turn, result in reduced obesity risks. However, there is an increasing number of research studies that have linked increasing health benefits from organic food consumption. In a recent experiment, Hyland et al. (2019) measured the pesticide metabolite levels of 16 individuals before and after switching to an all-organic diet. They found that the level of synthetic pesticides in all participants has dropped, on average, 60.5% after eating only organic just for 6 days. A recent comprehensive discussion of organic food benefits for human health is also found in Vigar et al. (2020). By increasing the consumption of organic food, people can improve their health and well-being. Thus,

(1) **Social performance** accounts for organic product consumption and is defined as:

$$Soc_{sc}(y) = N_m^o(y); \quad (4.6)$$

Where, $N_m^o(y)$ is the number of organic consumers in year y. Rohmer, Gerdessen & Claassen (2019) and Sazvar, Rahmani & Govindan (2018) used similar diet-related indicators such as nutritional compliance (i.e., amount of nutrient n consumed) and individual health-living environmental health (i.e., organic product consumption and production) to assess the performance of SSC in terms of public health.

With regard to environmental issues, this study focuses on the size of land used for organic farming practices. The heavy use of pesticides and synthetic fertilizers in conventional farming is seen as a major cause for more than 40% decline in the number of insects, and if this trend continues, there may be no insects left in the next 100 years (Stepanian et al. 2020). Adoption of organic farming can help to: protect soil quality, keep waterways clean, and preserve the landscape. Certainly, organic farming can reduce environmental impacts related to toxicity, and it could also help in biodiversity preservation.

(2) **Environmental performance** measures the size of organic farming and is defined as:

$$Env_{sc}(y) = \sum_{1}^{f'} \lambda_f^o(y); \tag{4.7}$$

Where $\lambda_f^o(y)$ is the total land used for organic farming in year y.

We consider the revenue obtained from the sale of organic food products as an indication of economic performance. While SC cost is the most commonly used indicator, this research focuses on green economic growth and fostering the income from green products. Thus,

(3) **Economic performance** evaluates organic income and is defined as:

$$Eco_{sc}(y) = \sum_{1}^{r'} P_r^o(y); \tag{4.8}$$

Where, $P_r^o(y)$ is the total sales of organic wine in year y, calculated as $D_r^o(d)P^o(\omega)$.

Given the difficulties associated with the quantification of behavior, farmers' goals and expectations of organic farming adoption. According to Bouttes, San Cristobal & Martin (2018), organic farmers' work enjoyment is determined by their expectations of organic farming conversions, "a satisfaction heightened by the positive feedback they already receive for their decision to convert." In transitioning to more ecological farming practices, the market feedback (in terms of price incentives offered by consumers) is essential to enable farmers to enhance adaptive capacity, recover from current setbacks and cope with future change. Thus,

(4) **Behavioral performance** is defined as:

$$Behav_{sc}(y) = \sum_{1}^{f'} A_f^o(y); \tag{4.9}$$

Where, $A_f^o(y)$ is the value-based expectations of farmers about organic farming in year y from (4.2).

4.4. Case study description

The general model described in Section 4.4.3 is applied to a case study derived from Australian wine industry. Currently, less than 0.5% of grape production volume in the Australian wine market belongs to organic wine, and the total global organic vine area reached 400,000 hectares in 2017 (Wine Australia, 2017). Most of the certified organic wines are exported to Europe (78%, mostly Sweden, UK) and the United States (12%). According to a recent report of Wine Australia (2019), the percentage of Australians who "sought to purchase any organic wine in the past six months" is approximately 20%. Despite the growing interest in the global market, still, organic wine remains a niche segment in the domestic market. Given this dependency of the primary organic production on the end consumer preferences, we take this case to illustrate the methodological added value of the ESSC. As shown in Figure 4.8, the ESSC has different aggregation levels, varying from individuals (e.g., consumers) to businesses (e.g., retailers, winery) and to farmers. Note that this is not a literal description of the Australian wine economy, and there are no specific assumptions apart from general connections between layers. The time step for the model is one week, as it is the basic time unit that corresponds to the wine shopping frequency reported by most of the households - once per week. In general, the economic life of the grapevines is up to 30-40 years (Carbone, Quici & Pica 2019), and thus the simulation runs for 30 years. For a complete description of data input that we have collected from literature and field, please refer to Appendix 4.B.

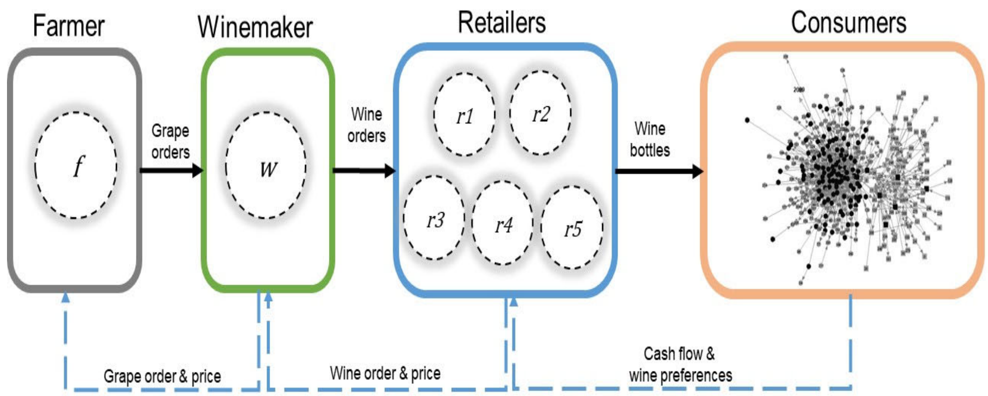

Figure 4.8. A presentation of ESSC model for the case study; black and grey dots indicate the heterogeneity of consumers, and the connections symbolize social networks.

The focus of our study was on understanding the collective impact of individual behavior change on the performance of the supply chain. In doing so, we have modeled disaggregated demand using ABM as the best option. DES and SD enabled us to simulate their processes involved and a workable mental model for farmers at the aggregated level. With regard to farmers and winemakers, we aimed at presenting the usual operations and practices in the region. So, in the model, we use a representative farmer agent and a winemaker agent with the characteristics of the cool-climate grape growers in South Australia and the typical processes of its commercial wineries, where we had collected empirical data. This region alone is responsible for more than half of the production of all Australian wines. While we acknowledge that more than sixty different species of grapevines exist in the Australian vineyards, for simplification, we collect data on one popular type, Cabernet Sauvignon (yield of organic/conventional land, resource requirements, and operational costs) (refer to Appendix 4.B.1).

Usually, wineries are established in the grape-producing zones to reduce transportation costs and preserve the quality of crops. The winery warehouses, however, may be located far from production sites and closer to customer zones. We assume that the winery warehouse, located in the vicinity of the retailers, uses a logistic system of the truck scale to distribute the products (refer to Appendix 4.B.2). There are five retailers in the model illustrating major Australian alcohol market players (including Woolworths, Coles Group, Metcash Limited, Aldi, and others). Each retailer has at least one shop in the City of Sydney Local Government Area (LGA). The average price of organic and conventional wines (tax included) across all stores is $13.00 and $10.00 per bottle, respectively. These prices are aligned with the average price of organic and conventional wines presented on Wine Australia website (https://www.wineaustralia.com). On top of retailing costs, the Australian wine retailers should pay Wine Equalisation Tax (WET) (29% of half the price of wine) and Goods and Service Tax (GST) (GST is 10% of the full price) to the governing body (refer to Appendix 4.B.3). The wine preference of 2099 households reported in Ogbeide (2013a) is used for the consumer agent. Readers can find the details of ORVin data in Appendix C of Taghikhah et al. (2020).

4.5. Results and discussion

4.5.1. Model calibration and validation

Calibration is a vital step in tuning the model to reproduce empirical data by tweaking the values of some of the model parameters. There was only a limited number of experimental results that we could use for this purpose. From Ogbeide (2013a), we had the number of consumers having a positive attitude towards organic wine, and from the Wine Intelligence (2018) survey, we could estimate the ratio of organic to conventional wine consumers. These numbers were used for calibrating the model. A list of calibrated parameters is presented in Appendix 4.C.

Where possible we use the real-world data (secondary collected elsewhere for other purposes, and primarily derived from expert interviews with wine and organic industry analysts) complemented with our assumptions about particular parameter values (explicitly discussed through the paper and tested on sensitivity) where data was lacking (refer to Appendix 4.C). Given the methodological focus of the paper – to illustrate the dynamics of supply chains integrated with the behaviorally-rich representation of consumers who follow empirical behavioral traits from the survey, usually omitted from the theoretical mathematical models– it is important to understand where and how the results of the ESCC differ from the conventional representation of a consumer. Hence, according to the case study categorization of Brailsford et al. (2019) for hybrid modeling, our model follows a mixed real-world and illustrative approach to explore the behavior of the integrated ESSC rather than to predict it in application to a particular case.

Figure 4.9 presents the calibrated number of organic wine consumers (153 consumers equal to 7-8% reported market size) in 20 runs. The variations in the demand are caused by the stochasticity of supply levels, product availability in different shops, and behavioral parameters. The land used for organic farming is 0.58 (hectare) and the annual sales of organic products stay around AU$ 38,334.

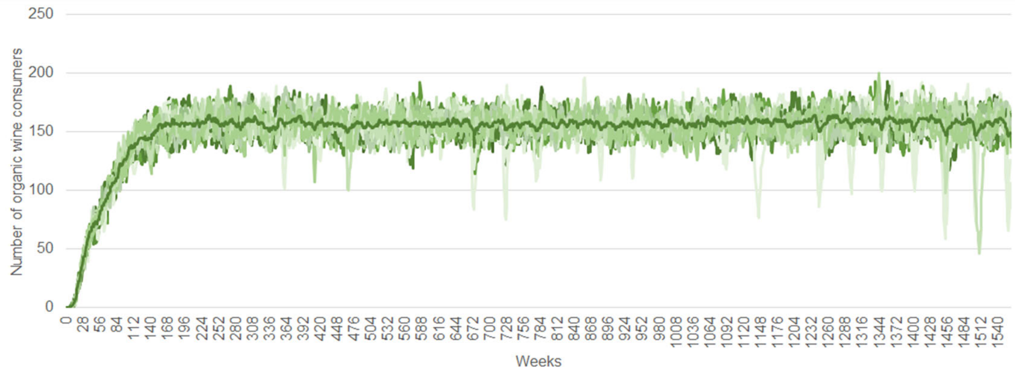

Figure 4.9. The number of organic wine consumers in the baseline scenario after 20 runs. The considerable variation in output is due to the stochastic nature of some of the parameters

As our model has three ABM, SD, and DES methods, the validation process was not straightforward. The problem of verification and validation of hybrid models have been extensively discussed in Brailsford et al. (2019). Nevertheless, we did address validation aspect as indicated in the following.

ABM for consumer model has already been validated by Taghikhah, Voinov, et al. (2020a) using aggregated results that reproduce observed data. The consumer survey by Ogbeide (2013a) also contained the number of consumers intending to purchase organic wine, when the price of organic wine is set to AU$12, AU$13, and AU$14. This data was not used for calibration purposes and was set aside to revalidate the model.

A comparison between the estimated number of consumers intending to purchase organic wine and the empirical data from literature is reported in Table 4.1. The results from the simulation model can estimate the number of organic wine consumers with high accuracy, translating to an error between 3% and 18%, depending on the willingness-to-pay settings.

Table 4.1. Model validation results, when comparing the number of consumers intending to purchase organic wine when its price is set to AU$12 (20% more), AU$13 (30% more), and AU$14 (40% more).

Validation scenarios	**Empirical number of organic wine consumers (Ogbeide 2013a)**	**Estimated number of organic wine consumers (model output)**	**Estimation error (%)**
Willingness to pay 20% more	467	453	-3%
Willingness to pay 30% more	279	258	-8%
Willingness to pay 40% more	150	177	+18%

For the DES model of vineyard process and outputs, we consulted industrial experts in the field of organic food science and agriculture and made presentations at conferences and meetings. We also tested the performance of model using extreme scenarios, for example, maximum and minimum prices for wine, maximum and minimum values for yields of vineyards, maximum and minimum values for statistical process control.

4.5.2. Uncertainty analysis

4.5.2.1. Local sensitivity analysis

Because of the overall model complexity, we used the one-factor-at-a-time (OFAT) method to calculate the sensitivity of model outputs to the input parameters. We analyze the model outputs by varying the model inputs by +/-20% of their base case values.

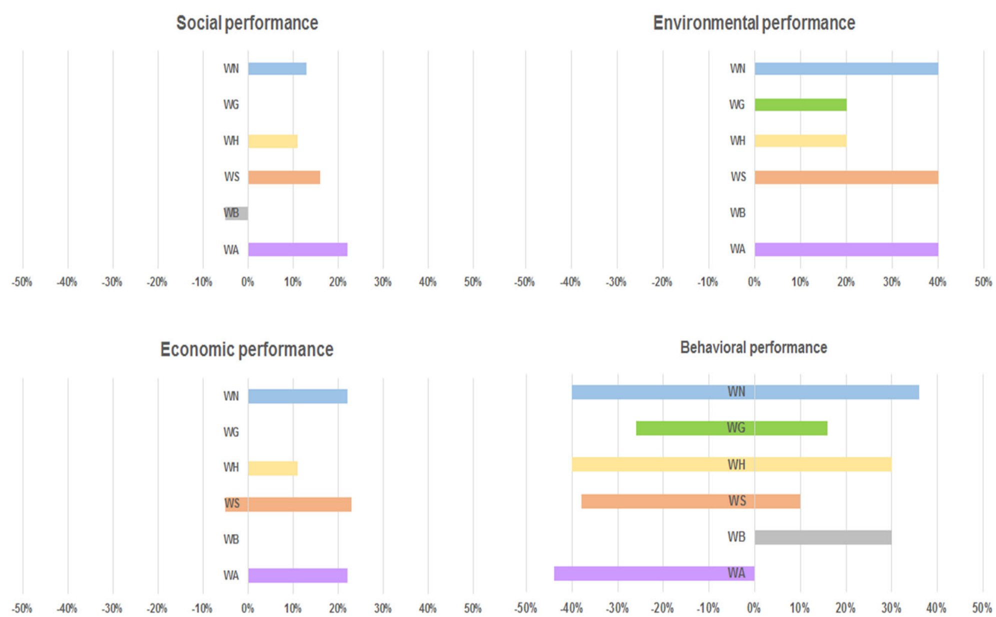

Figure 4.10. Sensitivity analysis of model estimations to the input parameters (details are presented in Appendix 4.D, Table 4.D1).

For example, Figure 4.10 presents the sensitivity of model results to variations in the weights of attitude (*WA*), PBC (*WB*), social norms (*WS*), hedonic goals (*WH*), gain goals (*WG*), and normative goals (*WN*). For a detailed discussion on these weights, we refer the readers to Appendix 4.C.3.3 in (Taghikhah, Voinov, et al. 2020a). Variations of less than 5% are excluded from the charts. Overall, social and economic performance have the lowest sensitivity to the inputs, while environmental and behavioral performance undergo significant variations. WA and WS account for the highest changes in social and economic performance, respectively (+22% ([18%, 24%] at 95% confidence interval (CI)) and +23% ([20%, 27%] at 95% CI) compared to the baseline). The value of environmental performance is equally sensitive to WA, WS, and WN parameters (+40% ([39%, 41%] at 95% CI) of the baseline estimation). The behavioral performance shows high sensitivity, nearly ±40%, to the dynamics of WN and WH. Appendix 4.D provides a detailed explanation of the modified parameters and their influence on the results.

From this uncertainty analysis, we can conclude that while the model is statistically sensitive to some parameters (e.g., WA, WH, and WN), overall, the model outputs (such as economic, social, environmental, and behavioral performance) are quite robust, stay within 95% CI limit and the trajectories do not go to infinity or fall to zero. This also helps us to target particular types of parameters for future refinement in empirical studies. For example, given that the model outputs are especially sensitive to social norms, more effort could be spent on improving empirical micro-foundations for this parameter. Conducting a global sensitivity analysis on this computationally-intensive model to assess the variations in the outputs to a combination of changing input parameters requires a high-performance computer cluster and will remain a subject for future work. The model is programmed in AnyLogic 8.3 simulation software with the help of agent-based, process-centric, and system dynamics modeling approaches. See Section 3 for more details on accessing the files.

4.5.2.2. Structural sensitivity of the model

When proposing the ESSC approach instead of the more traditional SSC analysis (Taghikhah, Voinov & Shukla 2019a), we assumed that the introduction of consumer behavior and preferences can have an impact on the overall performance of the SC. Here, with the model in place, we can actually see how such a structural change in the way the SC is defined impacts the main performance indicators. In the majority of proposed models in the literature on SSC, the demand for products is homogenous. In contrast, the ESSC accounts for heterogeneous demand. To turn our ESSC model into a more conventional SSC one, we replace the heterogeneous adaptive consumers with homogeneous and rational ones using the average weekly demands for organic and conventional wines in each retailer. The SSC assumption is that the demands are constant in time, homogeneous and independent of supply levels, and price of wines.

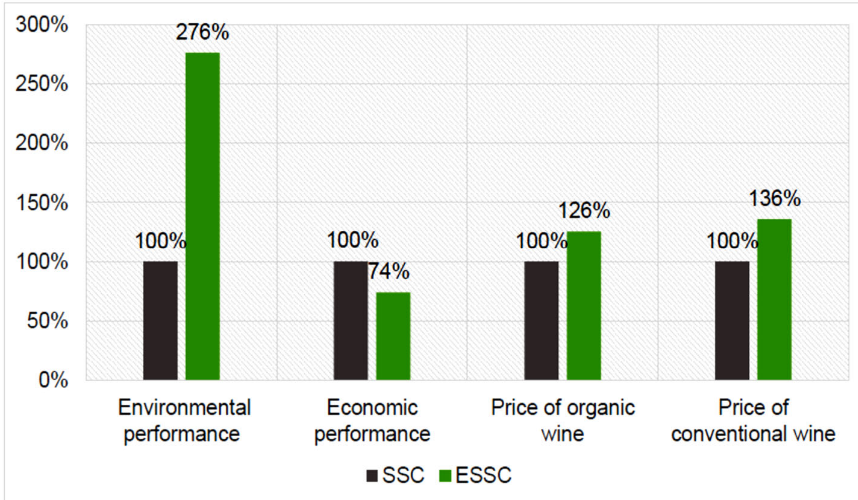

Figure 4.11. A comparison between the proposed ESSC and SSC (homogeneous demand).

We scale the value of SSC outputs to 100% and compare them with the baseline values of ESSC as presented in Figure 4.11. Behavioural performance is excluded from the analysis because SSC does not account for farmers' expectations. It can be seen that there are significant differences between the outputs of SSC and ESSC in terms of environmental (+176% points) and economic performance (-26% points). In the case of SSC, since the dynamics of wine prices do not affect the demand, the sales of organic wine would be higher than ESSC, even if the price of products (organic wine (-26% points) and conventional wine (-36% points)) are lower. This analysis shows that in the absence of heterogeneous demand, farmers do not perceive the market value of organic products, and they may decide to revert to conventional farming as reflected in the environmental performance.

4.5.3. Scenario analysis

Once the model is tested and displays reliable and meaningful performance, it can be used to explore the impact of various control factors on the overall dynamics of the system. This can help us to test how the system reacts to various combinations of input functions and parameters, which we call scenarios, and which describe management decisions and possible system modifications. There are many ways the system can be manipulated, and many policies and management interventions that can be explored. This is a subject of separate research; here, our purpose is only to demonstrate how ESSC can be used in industry and policy design and to show its receptivity to market feedback.

4.5.3.1. Scenarios related to consumer economic status and social networks

In this research, we consider an approach for scenario use, which was proposed in Kunc & O'brien (2017). They provided a practical framework for supporting the strategic performance of a firm by exploring firm's resources and capabilities. Based on this approach, we have designed a set of scenarios considering the opportunities and threats of SC in the external environment in conjunction with the dynamics of its strengths and weaknesses. Gu & Kunc (2019) also developed a hybrid simulation model for a supermarket SC and adopted a similar approach in devising strategies. For the purpose of this study, we only discuss the demand-side scenarios describing two possible changes in demographics (economic status such as income) and behavior (social networks such as neighborhood effect) of the consumers and compare the results to the baseline model output presented above in Section 4.5.2.1.

Scenario 1: There is a 20% increase in the number of middle and high-income consumers. In terms of model parameters, this means that the income of 14% of consumers earning up to AU\$100,000 per year (middle-income group) is increased to AU\$150,000 per year (high-income group). At the same time, the income of 6% of consumers earning up to AU\$50,000 per year (low-income group) is increased to AU\$100,000 per year (middle-income group). This is consistent with the growing trend in Australia. Currently, the production rate of organic wine is low, and on the contrary, the production rate of conventional wine is high. To comply with the possible growth in the consumption of organics in the near future, due to the increasing marginal utility of income, the SC cannot immediately respond to the demand and requires a three-year transition period from conventional to organic wine production. It can be considered as a weakness-opportunity strategy;

Scenario 2: The effect of neighborhood-level characteristics on the wine preference of consumers is restricted because there are increasing trends in people living in apartments and therefore are less likely to interact with each other on a regular basis. In fact, Sydney's urban population has moved towards apartment living to meet the affordable housing needs of the growing population. This change hinders social gatherings and neighbor interactions so that the influence of social norms on wine preferences becomes minimal. In terms of model parameters, this means that the weight of social norms on intention is changed from 0.12 to 0.02. As the word-of-mouth effect is small, the SC can shift the norm for conventional to organic wine purchasing, from a vicious into a virtuous cycle. This shift can perhaps bring higher socio-economic benefits for the business. It can be considered as a strength-threat strategy. Appendix 4.E provides a detailed explanation of the neighborhood effect and its sensitivity defined in this model (please refer to Figure 4.10).

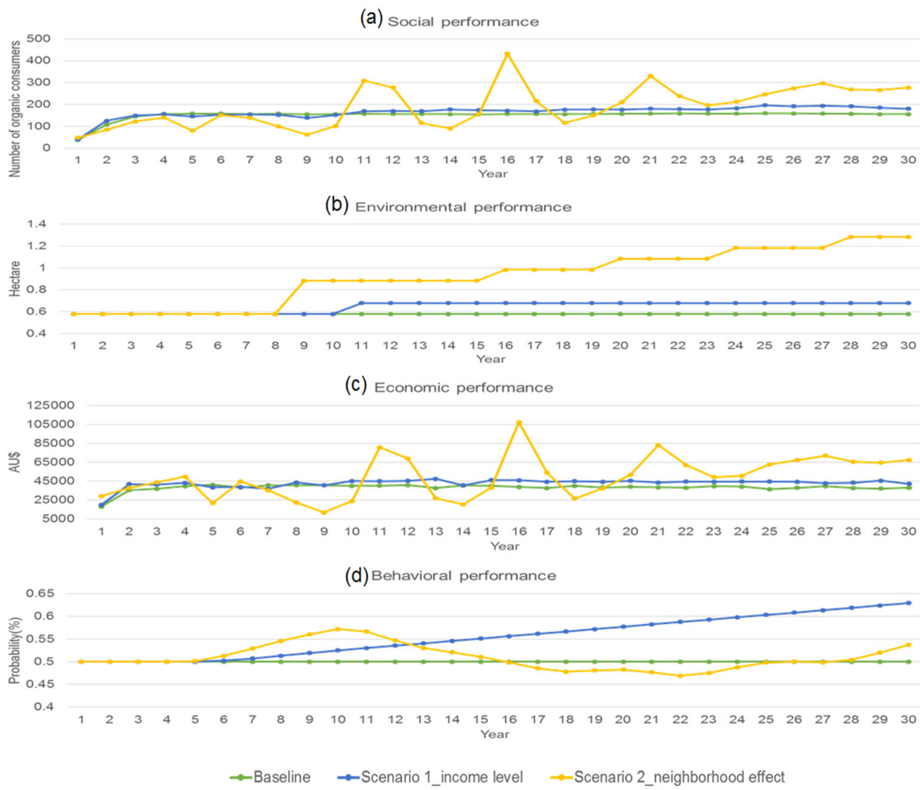

Figure 4.12. A comparison of scenario results with ESSC baseline.

The results presented in Figure 4.12 show that in scenario 2 all the indicators, except behavioral performance, perform better than in scenario 1. By reducing the influence of social interactions (among customers living in a neighborhood) on the wine purchasing decisions, the social, environmental, and economic performance of ESSC can be improved by 78%, 122%, and 76%, respectively. However, due to the market volatility caused by variations in the price of organic products and correlated changes of demand and supply, farmers' expectations of the value of organic farming do not grow significantly (Figure 4.12d). These dynamics are the result of conventional wine overstocking, and organic wine understocking caused mainly by the three year conversion period.

On the contrary, in scenario 1, we observe a growth in the organic market size by 17% in year 14 that eventually leads to a gradual increase in the farmers' expectations of organic agriculture value by 25% in year 30. With regard to environmental and economic performance, there is a 17% and 22% growth in scenario 1. The market financial incentive, in this case, is not good enough yet to meet the expectations of farmers regarding the value of organic farming, and hence government support is required.

From these production-consumption patterns, we may conclude:

- There is a negative impact of uncertain prices on farmers' expectations of organic adoption: The unpredictable and erratic organic prices add uncertainty to farmers' expectations about future returns. As it is unclear when organic wine prices would recover or stabilize, farmers start to prefer conventional markets more. They could choose to enter organic markets if the price for organic wine rose and remained relatively stable following the conversion from conventional farming. Thus, in the periods of the high volatility of organic wine price but the stability of conventional price, farmers tend to perceive the value of waiting to convert higher and risks in the future of organic farming lower.

- The propagation of consumer organic preferences through agro-food SC is slow: The adaptation of SC operations to the dynamic market trends can be delayed. For example, in both scenarios of simulation, the changes in the environmental and behavioral performance have started 5 to 10 years after the start of simulation. As there are two echelons between the consumers and farmers, transmitting the feedback/ market signals from the preferences of consumers to the land management decisions of farmers comes with a delay. Taylor (2006) and Naik & Suresh (2018) emphasize that the operational and structural factors such as long lead times, absence of long-term demand forecasts, etc. account for this gap between agricultural production and consumer demand.

- Social norms can trigger big shifts in consumer wine preferences: It is interesting to observe that minor changes in the consumption side parameters can help to improve the socio-environmental performance of agro-food SC. The social norms manipulation (reducing neighborhood effect) promotes ecological behavior more significantly than economic factors (consumer income growth). It is quite challenging to motivate consumers to spend more on organic products in the absence of supportive norms, even if their income level is higher. As social norms exert a strong effect on food consumption and production behavior, considering them in the management of SSC can provide new insights.

4.5.3.2. Single objective optimization

Despite the ESSC model is quite complex, we can still use it for purposes of optimization. In analyzing the possible optimized scenarios, we can find the optimal organic and conventional wine prices for maximizing social, environmental, economic, and behavioral performance separately. These experiments demonstrate the capability and flexibility of the proposed ESSC model.

Table 4.2. Payoff table for single-objective optimization.

	Single objective optimization				**Decision variables**	
	Social performance (%)	*Environmental performance (%)*	*Economic performance (%)*	*Behavioral performance (%)*	*Initial price of organic wine (price at equilibrium)*	*Initial price of conventional wine (price at equilibrium)*
Social performance	**73% (268)**	120% (2.04)	36% (52035)	-54% (0.23)	*10(9)*	*18(7)*
Environmental performance	73% (268)	**120% (2.04)**	36% (52035)	-54% (0.23)	*10(9)*	*18(7)*
Economic performance	-68% (50)	74% (1.01)	**67% (64,139)**	+14% (0.57)	*20(17.35)*	*17(8.5)*
Behavioral performance	-68% (50)	-47% (0.31)	-75% (9,159)	**+100% (1)**	*19(14)*	*7(7)*

Table 4.2 reports the results of four single-objective optimization tasks (maximizing one at a time) in percentages to baseline values after 20 runs. It should be noted that these best solutions might be local optima, not global solutions, but this does demonstrate how optimization can be used with the model developed. Comparing the results, we see that environmental performance shows the biggest potential for improvement, increasing by 120% from the baseline value, while economic performance has the smallest potential for improvement with only 67% increase. Moreover, the optimal results for social and environmental performance turn out to be the same, indicating that we can simultaneously increase the number of organic wine consumers and expand the organically certified land, while also enhancing the organic sales income by 36% in comparison to the baseline.

4.6. Conclusions and implications

Organic farming is a promising solution for moderating agriculture impacts on ecosystems and improving human health. Despite the potential benefits that this method has for biodiversity and soil fertility, the global adoption rate of organic farming is still low. It has not become mainstream for two main reasons: (1) lower farm yield and higher production costs in comparison to intensive agriculture (Uematsu & Mishra 2012), and, as a result, (2) reliance on a niche segment of consumers and a small market share, as compared to conventional food (O'Mahony & Lobo 2017). A growing number of studies focuses on improving the productivity of organic agriculture from sustainability perspectives; yet, the relationships between the behavior of final consumers and the decisions of upstream supply chain actors, in this case, farmers, have been poorly analyzed (Naik & Suresh 2018; Taghikhah, Voinov & Shukla 2019a). We address this void by extending the analysis of traditional food SC to include the dynamics of consumers choices and preferences for organic versus conventional food, as recommended by the ESSC framework (Taghikhah, Voinov & Shukla 2019a). This study contributes to the existing literature in the following four ways:

- First of all, it links three very different areas that, to our knowledge, have not yet been synthesized in a modeling study: (i) supply chain design and production economy, (ii) sustainability considerations and, (ii) pro-environmental and pro-health behavior. The model designed to operationalize the ESSC framework in which the SC analysis is extended to explicitly consider the buying behavior of consumers. While there are a number of papers that empirically examine the influence of behavioral aspects of demand on a few elements of supply, we are not aware of any published study that analytically links the heterogeneity of consumers and their preferences to the entire supply chain operation.

- Secondly, to the best of our knowledge, this is the first study that incorporates the preferences of consumers for organic food as well as farmer decisions regarding organic farming adoption into a model of an agro-food SC. Organic supply chain modeling studies for reducing environmental impacts have largely ignored important socio-ecological issues related to consumers. In this study, we include the dynamics of consumer behavior (due to the changes in the social norms, willingness to pay more, the demand substitutions, etc.) and farmers' expectations (due to the changes in the price of products, organic versus conventional production, etc.).

- Thirdly, it contributes to the methodological development in the SSC field by extending it with the ESSC paradigm and proposing the integration of SD-DES-ABM methods to improve the decisions considering sustainable development goals. So far, systems thinking approaches are underrepresented in the context of SSC research (Rebs et al., 2018), while the field can benefit from integrated modeling solutions that account for the interplay between SC and sustainability aspects. In particular, the interactions between ABM and SD provide an opportunity for considering the dynamics of social sustainability by developing the direct formulation of population, in our case, both consumers and farmers. According to Brandenburg et al. (2014) and Brandenburg & Rebs (2015), the practice of social simulation in SSC studies is adopted less often.

- Fourthly, the novelty of our model lies in capturing the simultaneous interactions between different SC actors (defined as adaptive systems) at different spatial and temporal scales, providing further insights into how integrated modeling can assist in strategic planning and in addressing real-world business challenges as suggested by Kunc (2019). In our case, the behavioral aspects, as well as operational characteristics of the SC, are studied in the model. The analysis of the model occurs in different levels of detail: micro-processes for consumption, and macro-process for production. Businesses and producers can use the model for understanding consumers' preferences, estimate their future influence on the operation, and develop long-term plans for land management and adoption of technologies. The analysis can help them to make their business models more resilient to market shocks and signals.

ESSC requires further integration of consumer behavior models as sub-models with traditional SSC models. This integration not only reveals the unobserved heterogeneity of preferences in consumers but also discloses a two-way influence between consumption patterns and production-distribution decisions. We calibrate the proposed model and test the validity of the outputs with available empirical data. The validation process is not straightforward (Bert et al. 2014) and can certainly be improved in the future, as more data becomes available and the model undergoes further testing.

The comparison between the results of ESSC and SSC analyses indicates that the assumptions of homogeneity in consumer preferences may need to be reconsidered and released. The homogeneous demand assumption has the highest impact on environmental and economic performance. Our modeling experiments demonstrate the adaptiveness of ESSC model for market dynamics. The findings with respect to the changes in the financial and behavioral status of consumers, highlight the highest impact of changing social norms on improving the sustainability of the SC. As there are multiple actors between the consumers and suppliers, farmers' perceptions and expectations towards the value of organic-based agriculture may deviate notably from reality. Moreover, the adaptation of producers to market trends takes much time due to the delays in supply. The analysis of optimal scenarios produces solutions that can simultaneously improve the economic, social, and environmental performance but not behavioral performance. This means, that by the expansion of organic farming in response to the growing demands of organic consumers, a significant reduction in the organic wine prices will eventually occur, which may not be favorable for farmers.

Accounting for demand-side heterogeneity provides new insights into addressing sustainability issues in SCs. The results imply that the design of organic food policies aiming at behavioral changes should not be limited to financial incentives. In designing politically feasible policy options, paying attention to the social environment, public awareness, norm support cues, and cultural codes can reinforce the transition to organic agriculture. Accompanying information and value-based policy instruments may not only lead to the diffusion of organic food consumption but also increase the number of organic farms. Having said that, due to the presence of certain constraints and barriers (for example changing price and availability) a quick transition in organic consumption-production cannot be expected. Government price control schemes to control minimum or maximum prices and trade control to balance exports and imports can speed up the contribution from the demand side in reducing the environmental impacts of production.

A future research direction for this study is to apply the model for investigating the implications of social change for organic food development. One can use the strategy development protocol (Torres, Kunc & O'brien 2017) to generate scenarios in consultations with managers. In particular, the influence of green taxation schemes, informational marketing campaigns, and organic food promotions and incentives on the adaptive behavior of farmers and consumers can be further examined and assessed. Another example of such scenarios is to explore the impact of Covid-19, as the Reserve Bank of Australia forecasts that GDP will fall by 6% in 2020 with a slightly larger number of 7% for unemployment. At the same time, social norms probably play a less significant role in households' choices due to lock-down and social distancing. It is interesting and contemporaneous to quantitatively assess whether the negative effect of the pandemic on wealth can be overcome by reversing the norms. A potential extension of this model will include agroecological models of crop growth to forecast the farm yield with regards to the adopted farming system (i.e., organic, biodynamic, conventional, etc.) under changing climatic factors (i.e., temperature, humidity, rainfall, etc.). Another interesting area to explore is the heterogeneity of farmers regarding their expectations of organic farming adoption and their choice between different conversion strategies. The current model addresses farmers’ decision as primarily a financial one. However, it seems that ecological and health values also impact this decision, just as optimistic or pessimistic expectations on the growth of the ecological market. Future studies can explore how different assumptions on the susceptibility of farmers for such factors would cascade through the system. The model was developed for the wine case study, yet, it is generic enough to be used for studying a wide range of agro-food SCs that have similar characteristics such as tea and coffee SCs. With minor modifications, the model can be easily adapted for other agricultural products to explore ways for transitioning to organic farming. The analytical framework and suggested modeling approach can also be adopted by researchers to examine the adaptive behavior of the disaggregated, multi-scale tiers of the SC in other sectors. Finally, the model can be used as a decision support tool to help practitioners in designing evidence-based policies for organic food.

4.7. Author contributions

Conceptualization: F.T., A.V., N.S., T.F., and M.A.; methodology: F.T., A.V., N.S., and T.F.; software: F.T.; validation: F.T., A.V., and N.S.; data collection: F.T.; writing—original draft preparation: F.T.; writing—review and editing: F.T., A.V., N.S., T.F., M.A.; visualization, F.T.; supervision: F.T., A.V., N.S., and T.F.

Appendix 4.A: Agent behaviors and interactions

4.A.1. Agent type and behaviors

We describe the dynamic behavior of four agent types, including farmer (Section 4.A.1.1), winemaker (Section 4.A.1.2), retailer (Section 4.A.1.3), and consumer (4.A.1.4). In all the notations below, y, ω, d refer to year, week, and day, respectively. Index o stands for organic and c stands for conventional products.

4.A.1.1. Farmer agent

Farmers act as the first-tier suppliers in the model. They grow two types of grapes - organic and conventional, which are harvested once a year. Depending on the availability of arable land and the farming practice (organic versus conventional), each farmer agent has a distinct production capacity and unit operating cost. Table 4.A1 presents the notations used in this agent type.

Table 4.A1. Parameters and functions for farmer agent.

Notation	**Description**	**Unit**
Parameters		

F	A set of farmers $f \in F = \{1, \ldots, f'\}$	-
λ_f^T , λ_f^o , λ_f^c	Total agriculture land, the land used for harvesting organic, and conventional grapes in the first year by farmer *f*.	ha
Y_f^o, Y_f^c	The annual yield of organic and conventional grapes for farmer *f*.	ton/ha
C_f^o, C_f^c	Cost of organic and conventional wine production for farmer *f*.	\$/ton
Functions		
$\lambda_f^o(y)$, $\lambda_f^c(y)$	Land used for harvesting organic and conventional grapes by farmer *f* in year *y*.	ha
$G_f^o(y)$, $G_f^c(y)$	Total harvest of organic and conventional grape by farmer *f* in year *y*.	ton/year
$C_f(y)$	Total cost of grape production for farmer *f* in year *y*.	\$/ton
$\varphi_f^{o_{err}}(\omega)$	Error adjustment between the actual and perceptive value of organic wine at week ω.	-
$\varphi_f^{o_{out}}(\omega)$	Changes in the perceived price of organic wine at week ω.	-
$\varphi_f^{o_{in}}(\omega)$	Recorder changes in the value of organic wine in comparison to conventional wine at week ω.	-
$P^{o_{eqb}}(\omega)$,$P^{c_{eqb}}(\omega)$	The equilibrium prices of organic and conventional wine at week ω.	
$P^{o}(\omega)$, $P^{c}(\omega)$	The market prices of organic and conventional wine at week ω.	
$P'^{o}(\omega), P'^{c}(\omega)$	Value of organic and conventional wine based on prices at week ω.	-
$\alpha^o(\omega), \alpha^c(\omega)$	Changes in the price of organic and conventional wine at week ω.	-
t	Time adjustment in the model.	week
$A^o(y)$	Farmer expectations of adaptation value at year y.	-

The model assumes that farmers have fixed land area available to supply the grape requirements of wineries. Farmers are contracted by winemakers to grow grapes under a capacity guarantee contract-farming scheme. This contact determines the approximate volume and the type of grapes - organic and conventional - required for production.

In this study, organic farming refers to a method of crop production that relies on biological pest controls (e.g., cover crops, crop rotation), and organic fertilizers (e.g., manure). Conventional farming, in contrast, uses synthetic fertilizers, fungicides, and pesticides to maximize the vineyard yield. The organic farming system is considered more sustainable since it can keep soil healthy and maintain the productivity of the land. The simulation begins in springtime when the grapevines are in the bud break phase. In this phase, tiny buds start to swell and eventually shoots grow from the buds. Approximately 40-80 days later, small flower clusters appear on the shoot, and the flowering phase starts. Soon after, 30 days on average, the flowers are pollinated, and the berries start to develop. This crop phase determines the potential yield of the vineyard. In the next phase, veraison, the color of grape berries changes after 40–50 days signaling the beginning of the ripening process. Following veraison, within 30 days, farmers complete the harvest, remove the grapes from the vine, and transport them to wineries for further processing. Due to the variation in climate conditions over the years, we consider a stochastic crop growth process where the annual harvest of organic and conventional grapes is:

$$G_f^o(y), G_f^c(y) = \{\lambda_f^o(y)Y_f^o, \lambda_f^c(y)Y_f^c\}; \qquad (4.A1)$$

Where, $\lambda_f^o(y), \lambda_f^c(y)$ are grape yields and Y_f^o, Y_f^c are cultivated areas at year y for organic and conventional grapes at farm *f*. It is to be noted that the total arable land is constant ($\lambda_f^o + \lambda_f^c = \lambda_f^T$).

The annual production cost at farm f is:

$$C_f(y) = [C_f^o \lambda_f^o(y) + C_f^c \lambda_f^c(y)]; \qquad (4.A2)$$

Where, C_f^o *and* C_f^c are unit production costs of organic and conventional grapes, respectively.

The transition from conventional to organic farming takes three years. The yield of transitioning farms should be sold as conventional products. This long lead time not only adds to the complication of balancing supply and demand but also gives a bias to the farmer judgments about the long-term cost-benefit of their organic vineyards. Farmer agents make judgmental assessments of the value of organic and conventional farming systems. The hypothesis of adaptive expectations (Nerlove 1958) states that the expectations of the future value of the interest variable depends on its past value and adjusts for the prediction error. Thus, the calculation of progressive expectations or error learning hypothesis is derived from observing the difference between past and present market values. The market and equilibrium price of organic and conventional wine guide farmers' expectations of adaptation to organic farming as shown in Figure 4.A1.

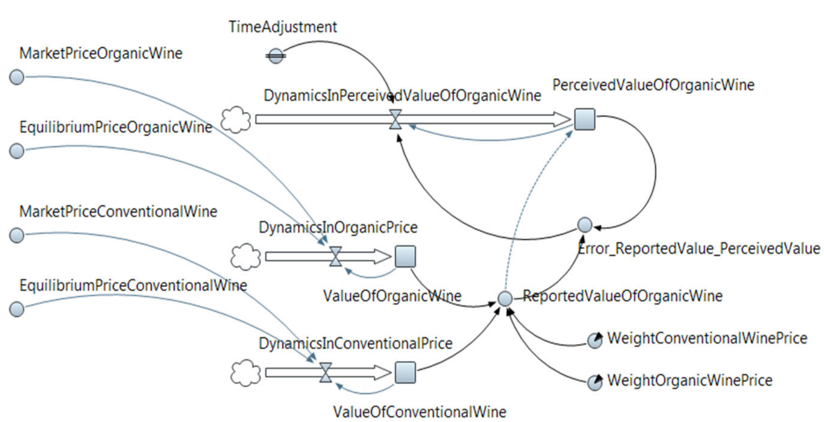

Figure 4.A1. Value-based expectations of farmers about the organic farming

The current expectations of the value of organic farming in the future is calculated as:

$$A_f^o(y) = \int_0^{\omega} \varphi_f^{o_{out}}(\omega) d\omega; \quad (4.A3)$$

$$\varphi^{\,o_{out}}(\omega) = \begin{cases} 0, & if\ (\varphi_f^{o_{out}}(\omega) \leq\ 0\ and\ \varphi_f^{o_{err}}(\omega)/t < 0)\ or\ if\ (\varphi_f^{o_{out}}(\omega) \geq 1\ and\ \varphi_f^{o_{err}}(\omega)/t\ > 0); \\ \varphi_f^{o_{err}}(\omega)/t, & else; \end{cases}$$

$$\varphi_f^{o_{err}}(\omega) = \ \varphi_f^{o_{in}}(\omega) - \varphi_f^{o_{out}}(\omega);$$

$$\varphi^{\,o_{in}}(\omega) = w^o P'^o(\omega) +\ w^c P'^c(\omega);$$

$$P'^o(\omega), P'^c(\omega) =\ \{\int_0^{\omega} \alpha^o d\omega, \int_0^{\omega} \alpha^c d\omega\};$$

$$\alpha^o(\omega), \alpha^c(\omega) \cong\ \{P^{o_{eqb}}(\omega), P^{c_{eqb}}(\omega),\ P^{o}(\omega),\ P^{c}(\omega)\};$$

Where $\varphi_f^{o_{out}}(\omega)$is the past perceived value of organic wine, $\varphi_f^{o_{err}}(\omega)$is the partial adjustment, which describes the gap between reported value $(\varphi_f^{o_{in}}(\omega))$ and the perceived value of organic wine. w^o and w^c refer to the weight of organic and conventional wine prices. They show the relative importance of wine prices for farmers (w^o+$w^c = 1$). Thus, $\varphi_f^{o_{in}}(\omega)$ is the weighted average of the perceived value of organic $(P'^o(\omega))$ and conventional wines $(P'^c(\omega))$. $\alpha^o(\omega), \alpha^c(\omega)$ are the expectations of wine prices in the future are influenced by the current market ($P^o(\omega)$, $P^c(\omega)$) and equilibrium ($P^{o_{eqb}}(\omega)$,$P^{c_{eqb}}(\omega)$) price of organic and conventional wines.

4.A.1.2 Winemaker agent

Winemaker agents process grapes to produce two types of products, organic and conventional wines. They are responsible for storing and dispatching final products to retailer agents. The total production capacity per agent is fixed, but periodically, the capacity ratio for organic and conventional wine production can adapt to the size of retailer orders.

Table 4.A2. Parameters and functions for winemaker agents.

Notation	Description	Unit
W	A set of winemakers $w \in W = \{1, \ldots, w'\}$	-
Parameters		
μ_w	The number of wine bottles winemaker *w* can produce per tonne of grapes.	bottle/ton
C_w^o, C_w^c	The total cost of producing organic and conventional wines by winemaker *w* (grape cost is excluded).	$/bottle

I_w^o, I_w^c	Inventory levels for organic and conventional wines at winery *w* warehouse in the first year.	bottle
$I_w^{o_{min}}$, $I_w^{c_{min}}$	Minimum inventory levels for organic and conventional wines at winery *w*.	bottle
Functions		
$F_w^o(y)$, $F_w^c(y)$	The total number of organic and conventional wine bottles produced by winemaker *w* in year *y*.	bottle
$I_w^o(d), I_w^c(d)$	Inventory levels of organic and conventional wines at winery *w* in day *d*.	bottle
$S_r^o(d), S_r^c(d)$	The average number of organic and conventional wine bottles that are ordered by retailer *r* in day *d*.	bottle
$C_w(y)$	Total cost of wine production for winemaker *w* in year y.	$

Due to perishability issues, winemakers try to process the grapes straight away after the harvest. The grapes get sorted, crushed and pressed, fermented, matured, and bottled as organic and conventional wines. Assuming winery *w* purchases all the farmer *f* yield, their annual production is:

$$F_w^o(y), F_w^c(y) = \{G_f^o(y)\mu_w, G_f^c(y)\mu_w\}; \qquad (4.A4)$$

Where $G_f^o(y)$and $G_f^o(y)$ are the availability of raw materials from (4.A1) and $\mu_w$is the capacity of processing facilities. While the same type of machinery can be used for producing organic and conventional wines, the processes (e.g., excluding sulfate during fermentation and bottling for organic wine) and associated costs might be slightly different. Thus, the annual production cost of winemaker *w* is:

$$C_w(y) = [C_w^o F_w^o(y) + C_w^c F_w^c(y)]; \qquad (4.A5)$$

Where, C_w^o, C_w^c are the costs of organic and conventional wine production at winery *w.*

Upon order arrival from retailers, the winemakers check for the requested wine types and the associated amounts. Based on the stock availability of each product type, they decide whether to fulfill the order (either entirely or partially) or reject it. Following a rule-based reasoning approach, different order fulfillment strategies are used by winemaker *w* to ship wine bottles to retailer *r* as described in Figure 4.A2.

$S_r^o(d)$, $S_r^c(d)$ are the order size of organic and conventional wine at retailer *r*, which will be described in 4.A.1.3. $I_w^o(d)\ and\ I_w^o(d)$ are the inventory levels at day *d* and $I_w^{o_{min}}\ and$ $I_w^{c_{min}}$ are the minimum inventory levels in winery *w.* If the order size of retailer *r* is within the inventory levels of winery *w* ($S_r^o(d) \leq I_w^o(d)$ and $S_r^c(d) \leq I_w^c(d)$) then, the order will be fully satisfied. The orders will be partially processed if the retailers' order size is smaller than the minimum inventories ($S_r^o(d)$ < $I_w^o(d)$ and $S_r^c(d) < I_w^c(d)$), or get rejected if otherwise. We consider an initial inventory level of $I_o$and I_c for all wineries to fulfill the orders in the first year (since there is no production during this period).

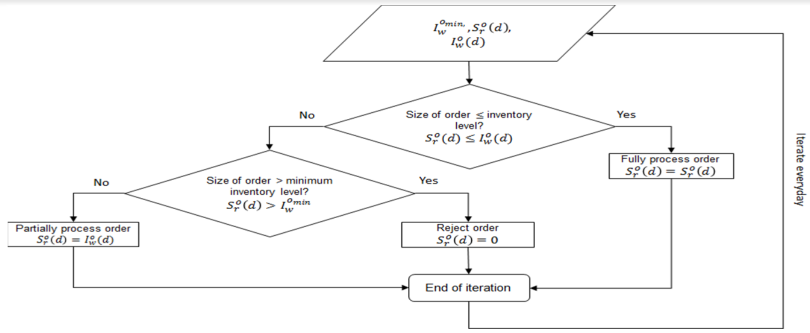

Figure 4.A2. Flowchart of organic wine order processing at winemaker agent (the same for conventional)

To prevent the issuance of new orders in case of no stock, winery *w* informs all the retailer agents that due to unavailability of stock $\{(I_w^o(d),\ I_w^c(d))$ < $(I_w^{o_{min}}\ ,\ I_w^{c_{min}})\}$, they would not accept further orders. This is done because wine production can take place once a year at the end of the harvest season. Before this time, any new order will be placed in the queue for processing when the product is available.

4.A.1.3. Retailer agent

Retailer agents have the responsibility of supplying products quickly and reliably, forecasting demand accurately, and controlling the inventory levels continuously. They employ dynamic inventory control models to make a trade-off between SC costs and demand fulfillment. Table 4.A3 summarises the parameters and functions used in describing this agent type.

Table 4.A3. Parameters and functions of retailer agent.

Notation	Description	Unit
R	A set of retailers $r \in R = \{1, \ldots, r'\}$	-
Parameter:		
I_r^o, I_r^c	The inventory level at retailer r on the first day of simulation.	bottle
O	Cost of ordering products.	\$/year
H	Annual holding cost of products.	\$/year
C_r^o, C_r^c	Cost of retailing one bottle of organic and conventional wines at retailer r.	\$/bottle
Functions:		
$I_r^o(d), I_r^c(d)$	Inventory levels for organic and conventional wines at retailer r in day d.	bottle
$I^o(d), I^c(d)$	Total inventory levels for organic and conventional wines in day d.	bottle
$B_r^o(d),\ B_r^c(d)$	The order backlog for organic and conventional wines in day d.	bottle
$D_r^{o_{avg}}(d), D_r^{c\_avg}(d)$	The average daily demand for organic and conventional wines at retailer r in day d.	bottle
$s_r^o(d), s_r^c(d)$	The reordering point for organic and conventional wines at retailer r in day d.	bottle
$Q_r^o(d),\ Q_r^c(d)$	Economic order quantity for organic and conventional wine for retailer r in day d.	bottle

$C_r(y)$	Total cost of inventory for retailer r in year y.	\$
$S_r^o(d), S_r^c(d)$	The average number of organic and conventional wine bottles that are ordered by retailer r in day d.	bottle
$L(h)$	Average lead time between placing an order and replenishment.	hour

The decisions on when to place an order and how many products to order from winemakers can impact the inventory-related costs. A continuous review inventory policy meets the requirements of retailers in response to dynamic demand situations (Hollier, Makj & Lam 1995). This policy allows them to review their inventory levels for both organic and conventional products daily. Figure 4.A3 displays the applied inventory control policy using a rule-based approach.

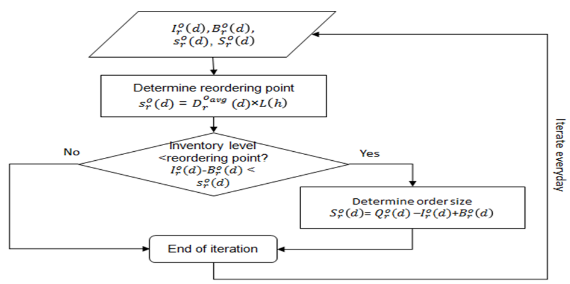

Figure 4.A3. Flowchart of organic order issuance at retailer agent (the same for conventional)

$s_r^o(d)$ and $s_r^c(d)$ are the reordering points for organic and conventional stocks to make sure that sufficient products are available to meet the demand before the order arrives at the retailer *r*. $I_r^o(d)$ *and* $I_r^c(d)$ are the current level of inventory and $B_r^o(d), B_r^c(d)$ are the number of lost sales for organic and conventional wines. $D_r^{o_{avg}}(d)$ *and* $D_r^{c_{avg}}(d)$ refer to the average daily demand for organic and conventional wine, and $L(h)$refers to the order lead time. This lead time is the sum of delays in the supply and logistics (e.g., the lags occur in production due to unavailability of raw materials, delays in loading/unloading orders, etc.).

If the organic or conventional wine inventory levels at retailer *r*, calculated as $I_r^o(d)$-$B_r^o(d)$ and $I_r^c(d)$-$B_r^c(d)$)), drop less than reordering points, then new orders should be issued. The order size at retailer *r* ($S_r^o(d)$, $S_r^c(d)$) depends upon the economic order quantity ($Q_r^o(d)$, $Q_r^c(d)$), the current level of inventory ($I_r^o(d)$, $I_r^c(d)$), and the number of lost sales ($B_r^o(d), B_r^c(d)$). The economic order quantity (Tersine & Tersine 1988) for retailer *r* is:

$$Q_r^o(d),\ Q_r^c(d) = \{\sqrt{[365 D_r^{o_{avg}}(d) O]/H},\ \sqrt{[365 D_r^{o_{avg}}(d) O]/H}\}; \qquad (4.A6)$$

Where O is the ordering and H is the holding cost. We assume ordering and holding costs in all the retailers are the same. The total costs of retailer r is:

Mathematically, the annual inventory costs of retailer *r* is:

$$C_r(y) = \sum_{365y}^{365(y+1)} \{[(D_r^{O_{avg}}(d) \times 365) / S_r^o(d)]\} + \{(D_r^{C_{avg}}(d) \times 365) / S_r^c(d)] \times O\} + \{[(S_r^o(d) + S_r^c(d)) / 2) \times H]\}; \quad (4.A7)$$

4.A.2 Agent interactions

4.A.2.1 Consumer-Retailer interactions

Retailer agents are gatekeepers between the producer and consumers. In interactions with consumer agents, retailer agents have multiple touchpoints to influence consumer preferences, including prices, and on-shelf availability. Table 4.A4 lists the notations used in explaining their relationship.

Table 4.A4. Notations relevant to the interactions of consumer and retailer agents.

Notation	Description	Unit
Parameters		
M	A set of consumer $m \in M = \{1, ..., m'\}$	-
ϑ	Minimum service level.	-
Functions		
$S_m^o(d)$,$S_m^c(d)$	Shopping size of organic and conventional wine for consumer m at day d.	Bottle
$H_m^o(d)$,$H_m^c(d)$	Consumer m habit of purchasing organic and conventional wine at day d.	-
$I_m^o(d)$,$I_m^c(d)$	Consumer m intention for purchasing organic and conventional wine at day d.	-
$N_m^{l_{avg}}(\omega)$	Total average number of consumers with lost demand at week ω.	-
$\vartheta_{\%}(\omega)$	Service level, the expected probability of not hitting a stock-out at week ω.	%
N_m^T	Total number of consumers.	-

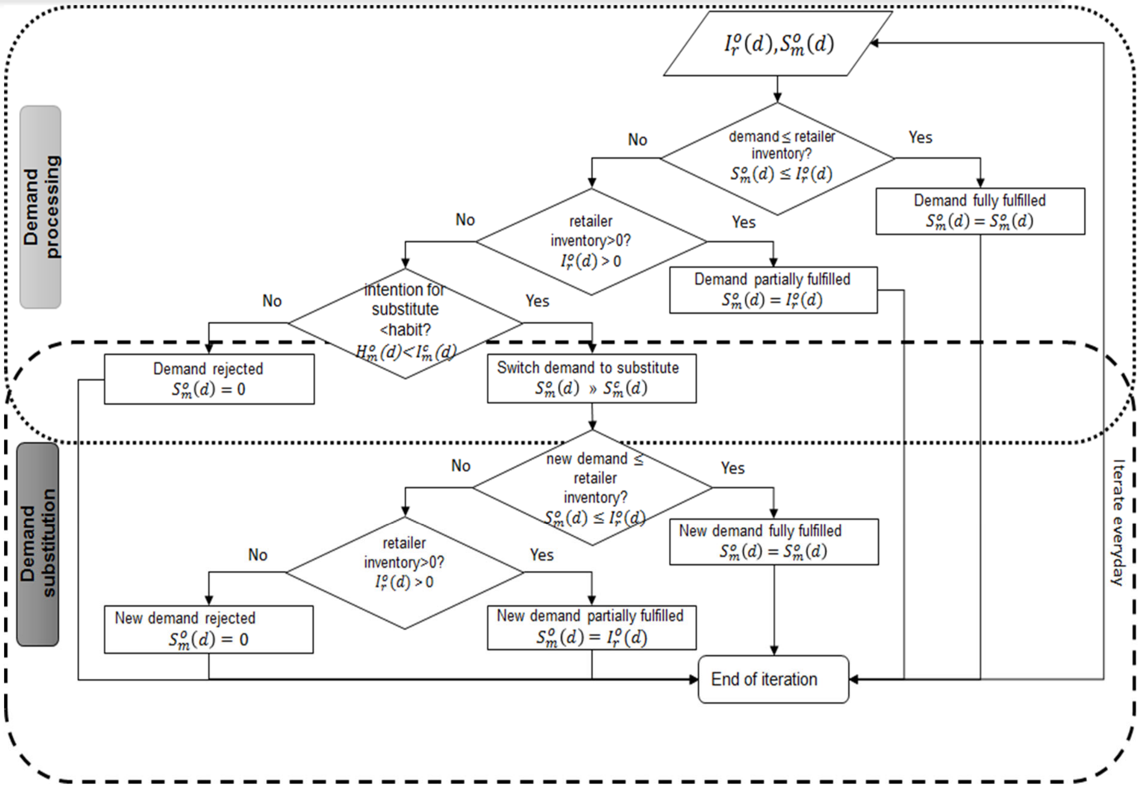

Figure 4.A4. Flowchart of interactions between consumers and retailers.

As shortages are allowed, when the consumer m demand ($S_m^o(d)$, $S_m^c(d)$) is higher than the inventory stock of retailer r, the demand is partially met (See Figure 4.A4). There are situations when wines of a certain type, for example, conventional ones, are not available at the shops. If consumer *m* habit of purchasing conventional wine is weaker than their intention to purchase organic wine ($H_m^c(d) < I_m^o(d)$), a shift in their preference (from conventional to organic wine) can occur that may lead to purchasing organic wine (also depending on the other factors).

4.A.2.2. Retailer-Winemaker interactions

Retailer agents interact with winemaker agents to control the production and manage the market demand by taking different pricing strategies for organic and conventional wines. Table 4.A5 provides a list of notations used to describe their relationship.

Table 4.A5. Notations relevant to the interactions of retailer and winemaker agents.

Notation	Description	Unit
Functions		
$\Delta F^o(y)$,$\Delta F^c(y)$	The growth in the total amount of organic land at year *y*.	ha
$\Delta F^o_{\%}(y)$,$\Delta F^c_{\%}(y)$	The percentage of organic land growth at year *y*.	%

$I_w^o(d), I_w^c(d)$	Inventory levels for organic and conventional wines at winery *w* at day *d*.	bottle
$F^o(y)$, $F^c(y)$	Total number of organic and conventional wine bottles produced at year *y*.	bottle
$P^{o_{min}}, P^{c_{min}}$, $P^{o_{max}}, P^{c_{max}}$	Minimum and maximum price of organic and conventional wines.	$/bottle
$P^{o_{eqb}}, P^{c_{eqb}}$	The equilibrium price of organic and conventional wine.	$/bottle
γ	Delays in changing the equilibrium price of wines.	week
R^o, R^c	The amount of changes in the price of organic and conventional wine.	$/bottle
$\zeta_{\%}^{o_{minmin}}, \zeta_{\%}^{o_{minmax}}$, $\zeta_{\%}^{o_{maxmin}}, \zeta_{\%}^{o_{maxmax}}$	Acceptance rates used for determining the minimum and maximum of lower and upper limits in organic control charts.	bottle
$\zeta_{\%}^{c_{minmin}}, \zeta_{\%}^{c_{minmax}}$, $\zeta_{\%}^{c_{maxmin}}, \zeta_{\%}^{c_{maxmax}}$	Acceptance rates used for determining the lower and upper limits of conventional control charts.	bottle
R'^o, R'''^o R'^c, R'''^c	The rate of increase and decrease in the equilibrium price of organic and conventional wine.	$/bottle
$I^o(d), I^c(d)$	Total inventory levels for organic and conventional wines at day *d*.	bottle
$\zeta^{o_{min}}(y), \zeta^{o_{max}}(y)$, $\zeta^{c_{min}}(y), \zeta^{c_{max}}(y)$	The upper and lower limits for controlling the supply of organic and conventional wines in the control charts at year *y.*	bottle

Retailer agents monitor the dynamics in the organic and conventional wine inventory stocks in the entire SC using statistical process control (SPC) charts. SPC is a statistical tool widely used for finding the variation causality and ensuring the controllability of processes in manufacturing (Oakland 2007). We consider two organic and conventional inventory control charts (at the retailer echelon) in the model. Upper and lower control limits for the wine inventory SPC charts are determined by retailers following production rules, as presented in Figure 4.A5.

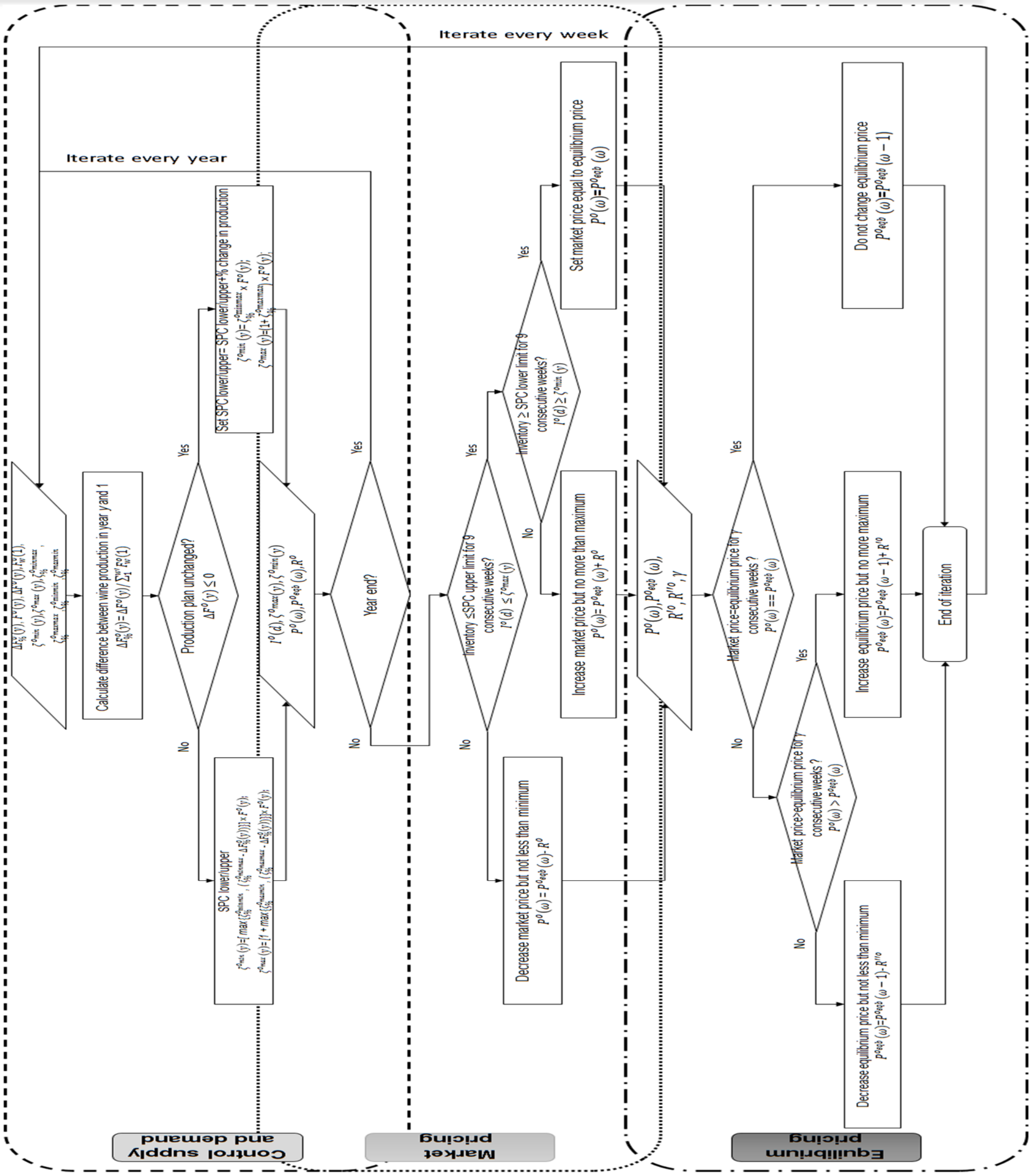

Figure 4.A5. Flowchart retailers and winemakers interaction.

The percentage of change in the production volume of organic and conventional wines at year y is:

$\Delta F^{o}_{\%}(y), \Delta F^{c}_{\%}(y) = \{\Delta F^{o}(y) - \Delta F^{o}(y-1), \Delta F^{c}(y) - \Delta F^{c}(y-1)\};$

$\Delta F^{o}(y), \Delta F^{c}(y) = \sum_{1}^{W'}\{(F^{o}_{W}(y) - F^{o}_{W}(1)), (F^{c}_{W}(y) - F^{c}_{W}(1)\};$ (4.A8)

$F^{o}_{W}(y)$ is from equation (4.A4) and $F^{c}_{W}(1)$ is the amount of grape production in the first year.

$\zeta^{o_{min}}(y), \zeta^{c_{min}}(y), \zeta^{o_{max}}(y), and\ \zeta^{c_{max}}(y)$ are the lower and upper limits of SPCs.

Standard upper and lower limit formulations are not suitable to be used in our case. The wine production occurs once a year during a couple of weeks so that the value of inventory levels during that period is far from the average inventory, and the calculated standard deviation is too high. Hence, if retailers determine control limits within three standard deviations of the average, variations in the process would not get recognized.

They are determined as a percentage of total wine production $\{F^o(y),\ F^c(y) = \sum_1^{w'}\big(F_w^o(y)\big), \sum_1^{w'}(F_w^c(y)\}$. These percentages are defined on a range of minimums and maximums as:

- The minimum percentage for lower limits on a range with a minimum($\zeta_{\%}^{o_{minmin}}$, $\zeta_{\%}^{c_{minmin}}$), and maximum ($\zeta_{\%}^{o_{minmax}}, \zeta_{\%}^{c_{minmax}}$) values, and
- The maximum percentage for upper limits on a range with a minimum($\zeta_{\%}^{o_{maxmin}}$, $\zeta_{\%}^{c_{maxmin}}$), and maximum $\big(\zeta_{\%}^{o_{maxmax}}, \zeta_{\%}^{c_{maxmax}}\big)$ values.

These SPC charts are used to monitor the dynamics of product inventories and customer demand. Nelson rule 8 is used to check whether the process is in control/out of control. Accordingly, if the inventory level is out of the defined upper and lower limits for at least nine consecutive time units, then the process is considered uncontrolled. The total weekly inventory levels of organic and conventional wine $(I^o(\omega), I^c(\omega))$ across the entire supply chain is calculated as in:

$$I^o(\omega), I^c(\omega) = \{\textstyle\sum_1^{r'} I_r^o(\omega), \sum_1^{w'} I_r^c(\omega)\}; \qquad (4.A9)$$

In uncontrolled situations, retailers change the market prices of products $(P^o(\omega), P^c(\omega))$ to rebalance the demand and supply. That is, oversupply leads to a drop in the market prices while undersupply increases the market prices of wines by a predetermined rate (R^o, R^c). The changes in the market price of wines cannot drop below the minimum $(P^o(\omega), P^c(\omega) \leq P^{o_{min}},\ P^{c_{min}})$ or go beyond the maximum price of wines $(P^o(\omega), P^c(\omega) \leq P^{o_{max}}, P^{c_{max}})$.

In this case, the price of products will change temporarily over a short period that may not be sufficient for coping with supply and demand imbalance. Price adjustment is an effective market mechanism aiming to tune the equilibrium prices $(P^{o_{eqb}}(\omega), P^{c_{eqb}}(\omega))$ for increasing or decreasing the sales of a product for longer periods. Instead of a fixed price option, wine equilibrium prices are modified on a γ week-by-week basis except during the land conversion period from conventional to organic. The rates of change (R'^o, R'^crefer to increasing rates and R''^o, R''^c refer to decreasing rate) in equilibrium prices of wine are set by retailers.

4.A.2.3. Winemaker-farmer interaction

A sequence of decisions winemakers and retailers make about the wine prices affects the production plans and supply agreements with farmers. When the price for a certain wine type increases, its production becomes financially more attractive and viable to winemakers. Thus, both parties decide on the volume and selling price of yield in a renewed contract farming agreement. Table 4.A6 provides a list of notations used for describing this interaction.

Table 4.A6. Notations relevant to the interactions between farmer and winemaker agents.

Notation	Description	Unit
Parameters:		
ρ	A monetary threshold above which winemakers find investment in organic wine production valuable (value per bottle is considered).	$/bottle
μ	The average number of wine bottles that winery w can produce per tonne of grapes.	Bottle/ton
Y^o	Average annual yield of organic grape production.	ton/ha
Ω^{min}	The minimum amount of conventional land farmers convert into organic in every conversion decision.	ha
w^o, w^c	The importance of changes in the price of organic and conventional wine.	-
Functions:		
$\chi^o(y)$	An approximation of land requirements for conversion into organic at year y.	ha
$\lambda^c_{\%}(y)$	The ratio of conventional land at year y.	%
$\Omega^o(y)$,$\Omega^c(y)$	The amount of conventional land farmers convert into organic and vice versa at year y.	ha
$\delta^o(y)$	The probability of organic grape failure at year y.	%
$F^o(y)$, $F^c(y)$	Total number of organic and conventional wine bottles produced at year *y*.	bottle
$N^o_m(\omega), N^o_{\%}(\omega)$	The number and the percentage of organic wine consumers at week ω.	
$\Delta P^o(y)$,$\Delta P^c(y)$	The dynamics of organic and conventional wine prices during year *y*.	

In making procurement-related decisions factors such as changes in the price of wines, service levels, and inventory management are important to be considered.

Convert from conventional to organic farming:

No changes in the production plan and vineyard configuration is expected unless the equilibrium price of organic wine increases before the planting season ($\Delta P^o(y)$>0 and at the same time $I^o(d) \leq [\zeta^{o_{max}}(y)]$).

The dynamics of organic and conventional wine price during year *y* is:

$\Delta P^o(y), \Delta P^c(y)$={ $\sum_{52y}^{52(y+1)}[P^o(\omega), -P^{o_{eqb}}(\omega)]$- $[P^c\ (\omega), P^{c_{eqb}}\ (\omega)]$}; (4.A10)

The organic conversion scale in year *y* is:

$$\Omega^{o}(y) = \begin{cases} \max\{\Omega^{min}, \chi^{o}(y)\}, & \text{if } (\delta^{o}(y) \leq 0.3); \\ \Omega^{min}, & \text{if } (0.3 < \delta^{o}(y) \leq 0.7); \\ \min\{\Omega^{min}, \chi^{o}(y)\}, & \text{if } (0.7 < \delta^{o}(y)); \end{cases} \qquad (4.A11)$$

Here, $\Omega^{min}$is the minimum conversion scale, $\chi^{o}(y)$ is the land required for conversion based on demand estimations and $\delta^{o}(t)$refers to the probability of organic sale failure.

The value of $\chi^{o}(y)$ depends on:

- Percentage of organic wine consumers ($N_{\%}^{o}(\omega) = N_{m}^{o}(\omega)/N_{m}^{T}$),
- Average organic grape yield ($Y^{o} = (\sum_{1}^{f'} Y_{f}^{o})/f'$),
- Percentage of available conventional land ($\lambda_{\%}^{c}(y) = [\sum_{1}^{f'} \lambda_{f}^{c}(y)]/[\sum_{1}^{f'} \lambda_{f}^{T}]$),
- The average capacity of wine production ($\mu = (\sum_{1}^{w'} \mu_{w})/w'$);

and is:

$$\chi^{o}(y) = \min\{([N_{\%}^{o} \times M^{n}(\omega) \times \lambda_{\%}^{c}(y)] / [Y^{o} \times \mu]), \Omega^{min}\}; \qquad (4.A12)$$

The value of $\delta^{o}(t)$ is:

- If $\{\Delta P^{o}(y) \geq \rho$ and $\vartheta_{\%}(\omega) \geq \vartheta$ and $\Delta P^{o}(y) \geq \Delta P^{c}(y)\}$ or $\{I^{c}(d) > [2 \times \zeta^{c_{max}}(y)]\}$, then, winemakers would sell organic wines at higher prices and the probability of organic sale failure is low ($\delta^{o}(t) \leq 0.3$).
- If $\{0 < \Delta P^{o}(\omega) < \rho$ and $\vartheta_{\%}(\omega) \geq \vartheta$ and $P^{o_{eqb}} < P^{o_{eqb}}(\omega)\}$ or $\{P^{c_{eqb}}(\omega) = P^{c_{min}}$ and $I^{c}(d) > \zeta^{c_{max}}(y)$ and $I^{o}(d) < 1.5 \times \zeta^{o_{max}}(y)\}$ or $\{\Delta P^{o}(y) \geq \rho$ and $\vartheta_{\%}(\omega) \geq \vartheta$ and $\Delta P^{o}(y) < \Delta P^{c}(y)\}$, then winemakers would not sell the organic wine at a higher price, but still, its production is comparatively more attractive. So, the probability of organic sale failure is moderate ($0.3 < \delta^{o}(y) \leq 0.7$).
- If $\{\Delta P^{o}(\omega) \geq \rho$ and $\vartheta_{\%}(\omega) < \vartheta\}$, then, the winemakers would invest further in producing organic wines carefully since the service level is already high. So, there is a high risk of organic sale failure ($0.7 < \delta^{o}(y)$).

Revert from organic to conventional farming:

The decisions on increasing the production volume of conventional wine and reverting from organic to conventional agriculture impose higher risks on the financial performance of SC. According to (Sahm et al. 2013), among all reasons for the revision, economic factors, and the fluctuation in the organic product prices play the main role. In this model, the dynamics of equilibrium price of organic and conventional play the main role in provoking the reversion decisions ($\Omega^c(y) = \Omega^{min}$) as:

- If there is no positive change in the organic wine price while the conventional price is increasing and the service level is less than the minimum acceptable level $\{\Delta P^o(y) \leq 0$ and $\vartheta_{\%}(\omega) \geq \vartheta$ and $\Delta P^c(y) \geq \rho\}$, or
- If there is an oversupply of organic wine and its price is at minimum $\{P^{o_{eqb}}(\omega) = P^{o_{min}}$ and $I^o(d) \geq 2 \times \zeta^{o_{max}}(y)\}$.

In all the other conditions, farmers do not change the vineyard configuration.

Appendix 4.B: Data input

4.B.1. Data input for farmer agent

The lowest level of model presentation at the farm level is the yield of organic and conventional grapes. Studies on the dynamics of yield under different farming systems in the Australian (Penfold et al. 2015), and the Italian vineyards (Pizzigallo, Granai & Borsa 2008), Niccolucci et al., (2008)) indicate that in comparison to conventional, organic agricultural systems tend to have approximately 20-30% harvest loss. According to the Australian National Vintage Report (Australia 2017, 2018) and South Australia Winegrape Crush Survey (Australia 2019a), the average yield of organic and conventional vineyards in cool climate regions are 7.5 and 9.5 (ton/hectare/year), respectively.

Table 4.B1 shows the annual operating costs of grape production (e.g., costs of fungicides, nutrition, herbicides, insecticides, labor, irrigation, and harvesting). South Australian vineyards report explains 10-30% higher costs for organic grape production mainly due to the increased costs of organic fertilizers, mowing and cultivation under-vine in organic/biodynamic vineyards (Nordblom et al. 2017; Penfold & Howie 2019; Wheeler & Crisp 2009; Wheeler & Crisp 2011).

Table 4.B1. Organic and conventional vineyard inputs and their associated costs.

Farm activity	Organic	Conventional
	(Nordblom et al. 2018; Nordblom et al. 2017; Penfold & Howie 2019; Penfold et al. 2015; Wheeler & Crisp 2011)	**(Australia 2017, 2018)**
Operating Costs	**($/ha)**	**($/ha)**
Fungicide application	304	299
Herbicide under-vine	-	82
Mowing mid-row	85	85
Mowing under-vine	41	-
Cultivation under-vine	487	-
Mechanical pruning	280	280
Herbicides		
Credit® (glyphosate)	-	33
Bonus® (adjuvant)	-	33
Goal® (oxyfluorfen)	-	3
Rifle®3 (pendimethalin)	-	63
Fungicides		
Unishield® Wettable Sulphur	30	29
Norshield WG® (copper cuprous oxide)	44	46
Flint®3 (trifloxystrobin)	-	18
Insecticide		
Proclaim®3 (emamectin benzoate)	-	27
Nutrition		
Fertilizer (UAN)	-	32.25
OFS Organic Nitrogen3	19	19
Seasol® (liquefied seaweed)	60	60
Irrigation	300	662.5
Harvesting	725	725
Electricity	150	250
Crop Insurance	301	296
Repairs and maintenance	400	400
Transport	518	518
Labor	1200	1000
Overhead costs	3000	2200
Total Costs ($/ha/Yr)	*7944*	*7160.75*

4.B.2. Data input for winemaker agent

Table 4.B1 shows a list of South Australian organic and conventional vineyard and winery inputs and their associated costs. Regarding processing parameters, we specify a triangular distribution with minimum 3, maximum 10, and mean 5 days to the production time, assuming that the juice is bottled right away after production. According to Wine Australia, wineries may produce approximately 60 cases or 720 bottles of wine from 1

ton of grapes. The average total cost of processing activities (including bottling, barreling, maturation, crush, ferment, pressing, clarification, blending, filtering, pressing, and racking) in large-scale wineries is nearly $2.6 and $2.3 per bottle of organic and conventional wine.

Table 4.B2. Production costs of winery

Winery activity	**Conventional**
Reference	(Australia 2016)
	($/Yr)
Bottling	$758
Barreling	$473
Maturation	$113
Destemming and crushing	$102
Alcoholic Fermentation	$102
Pressing (red)	$84
Clarification	$75
Racking (red)	$73
Blending	$47
Grape receival	$44
Filtering (white)	$30
Filtration	$29
Warehouse Dispatch	$29
Pressing (white)	$29
Cold Stabilisation	$19
Racking (white)	$18
Total costs ($/ton/Yr)	*$2,025*

Regarding logistics parameters, following a short delay, uniformly distributed between 1 and 2 hours for preparing the orders, the loaded trucks are sent to the retailers. Align with the average speed of transportation in NSW, the speed of trucks is set 70 kilometers per hour. On arrival to the retailer, the truck waits up to 1 to 2 hours to get unloaded. 13 trucks provide service in the logistics network to avoid stock out caused by transportation delays. In simulating the trucks in the logistics network, we consider parameters such as the capacity, speed, loading and unloading delays.

4.B.3. Data input for retailer agent

The average price of organic and conventional wines (tax included) across all stores is $13.00 and $10.00 per bottle. These prices are aligned with the average price of organic and conventional wines presented in Wine Australia Website. We consider the minimum selling price of organic and conventional wine in the local market equal to their equivalent export prices at $9 organic and $7 conventional wines ($/bottle) (Maret

Bulletin 2018). The service level for wine SC is usually determined as high as possible, around 95%. The average ordering cost and annual holding costs are approximated at \$50 (per order) and \$1 (per bottle/year). The wine retailers should also pay Wine Equalisation Tax (WET) on top of Goods and Service Tax (GST) levied at 29% and 10% respectively, to the governing body. These costs should be included in the retail costs. According to Australian Tax office (2019), the payable WET on sale of retailers is 29% of half the price of wine, and the payable GST is 10% of the full price.

Appendix 4.C: Calibration

Table 4.C1 provides a list of calibrated parameters and their best fitting values.

Table 4.C1. Calibrated parameters of the model and their best fitting values.

parameters	**Value**	**parameters**	**Value**	**parameters**	**value**
WA	0.55	$\zeta_{\%}^{o_{minmin}}$	0.05	R'^{o}	0.03
WB	0.6	$\zeta_{\%}^{o\_minmax}$	0.08	R''^{o}	0.05
WS	0.12	$\zeta_{\%}^{o_{maxmin}}$	0.3	R'^{c}	0.1
WH	0.4	$\zeta_{\%}^{o_{maxmax}}$	0.35	R''^{c}	0.25
WG	0.76	$\zeta_{\%}^{c\_minmin}$	0.05	$I_{w}^{o\_min}, I_{w}^{c\_min}$	10
WN	0.16	$\zeta_{\%}^{c\_maxmax}$	0.3	I_{r}^{c}	7,000
λ_{f}^{o}	0.58	Ω^{o_min}	0.1	I_{r}^{o}	150
λ_{f}^{c}	11.1	R^{o}	0.4	I_{w}^{o}	555
ρ	3	R^{c}	0.4	I_{w}^{c}	40,000

Across multiple retail agents, there are different on-the-shelf-availability for organic and conventional wines. Studies show that increasing the availability of organic food at shops could create a higher preference for healthy eating (He, Tucker, Gilliland, et al. 2012; He, Tucker, Irwin, et al. 2012). Similarly, for organic shopping behavior, availability is noted as a less influential factor (ranked fifth) in comparison to price (ranked first) (Lawson, Cosby, Baker, Shawn, et al. 2018). Accordingly, in PBC function of consumer agent, the weights of availability (W_{P2}) and price (W_{P1}) are set to 0.2 and 0.8, respectively.

Appendix 4.D: Sensitivity analysis

Figure 4.D1 displays the overall model sensitivity using One Factor At Time method. Obviously, farmers' adaptive expectations have the highest sensitivity to the model inputs. A list of parameters that caused the highest variations in the outputs is shown in Table 4.D1.

Table 4.D1. The sensitivity of input parameters on the model outputs.

Notation	**Value**	Social performance *(155)*	Behavioral performance *(0.5)*	Environmental performance (0.58)	Economic performance (	**Notation**	**Value**	Social performance *(155)*	Behavioral performance *(0.5)*	Environmental performance (0.58)	Economic performance (
WA	0.45 0.5 **0.55** 0.6 0.65	+10% 0 0 +20% +22%	-44% -40% 0 -12% 0	+20% +20% 0 +40% +40%	0 0 0 0 0	*WH*	0.61 0.68 **0.76** 0.84 0.91	0 0 0 +8% +11%	-40% -30% 0 +6% +30%	0 0 0 +20% +20%	0 0 0 0 0
WB	0.5 0.55 **0.6** 0.65 0.7	0 0 0 0 -5%	+30% 0 0 0 0	0 0 0 0 0	0 0 0 0 0	*WG*	0.3 0.35 **0.4** 0.45 0.5	0 0 0 0 0	-26% -20% 0 +16% 0	+20% +20% 0 0 0	0 0 0 0 0
WS	0.08 0.1 **0.12** 0.14 0.16	+16% +6% 0 0 +7%	0 +10% 0 -34% -38%	+40% +20% 0 0 +20%	+23% +12% 0 0 -5%	*WN*	0.12 0.14 **0.16** 0.18 0.2	+12% +13% 0 0 0	+36% 0 0 -30% -40%	+40% +40% 0 0 +20%	+22% +11% 0 0 0

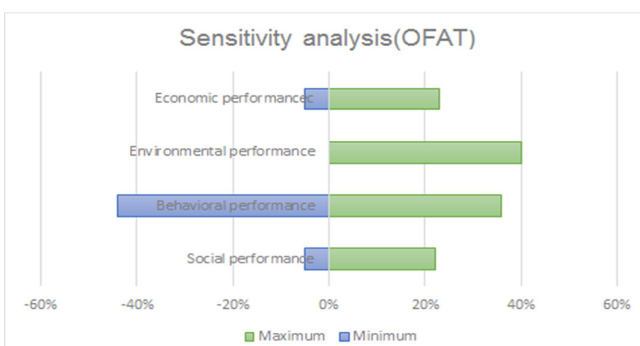

Figure 4.D1. The overall sensitivity of the model outputs

Appendix 4.E: Neighborhood effect

Looking into the existing literature on organic wine purchasing, we could not find any study reporting data on **social network** characteristics. Nevertheless, when it comes to alcohol drinking behavior, social disorganization theory (Sampson 1993) highlights the importance of neighborhood environments (Shih et al. 2017). So, the social network of each household (macro-level network) includes neighbors living up to 400-800 meters away from them. The defined neighborhood type and buffer may influence the estimation of neighborhood effects (i.e., the effect of a particular neighborhood characteristic on wine choice) (Duncan et al. 2013). Individual relationships with peers and friends may modify neighborhood effects but are not included here due to the lack of data. Hence, ORVin focuses only on social interactions with neighbors where households exchange information about wine preferences and continuously update their perceived subjective norms about wine types.

Drinking wine with friends, family, or workgroups internalizes the social norms for wine consumption and preferences in individuals. Although researchers have already shown a strong relationship between socio-cultural norms and drinking behavior (Nwagu, Dibia & Odo 2017; Sudhinaraset, Wigglesworth & Takeuchi 2016), there are a few studies examining the influence of social pressures on purchasing organic wine (Thøgersen 2002). Social desirability can be an impetus for consumers' wine choice, especially when a wine is purchased for particular occasions or as a gift. In these situations, people often seek to satisfy social norms rather than personal preferences. Boncinelli et al. (2019) report that on gift-giving occasions, the probability of choosing organic wine is much higher than personal use. Researchers such as Johe & Bhullar (2016) emphasize that subjective appraisals of a reference group are a crucial predictor of organic wine purchasing intention. Here, we examine the impact of subject norms on buying organic wine.

F_{Si}(t), the household i subjective wine norm at time t, is calculated as:

$$F_{Si}(t)=\frac{F_{Spoi}(t)}{F_{Spi}(t)}; \qquad (4.E1)$$

where $0 \leq F_{Si}(t) \leq 1$; i=1, …, n;

F_{Spoi}(t) is the number of neighbors with organic wine preferences and F_{Spi}(t) is the total number of household i's contact network at time t. F_{Si}(t) higher than 0.5 represents organic wine as the norm while values less than 0.5 indicate that conventional wine is the perceived subjective norm. 4.E1 determines which norm (i.e., organic or conventional) can guide a household decision to buy organic wine.

Chapter 5:

Data-driven Modeling for Consumer Behavior towards Purchasing Organic Food: A Case of Wine Industry

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Food Quality and Preference Journal (under review)

Abstract

Organic viticulture can provide healthier products while reducing environmental impacts. The organic market share may grow if consumer preferences shift demand to more organic products. This study empirically examined consumer planned, impulsive, and unplanned behavior when purchasing organic wine. To address various aspects of consumer behavior, we integrated the theory of planned behavior, theory of interpersonal behavior, impulsive buying theory, alphabet theory, and goal framing theory to identify possible influential cognitive and affective factors driving consumers' preferences. We designed and conducted a survey of 1003 Australian consumers in the city of Sydney. Analysis of the results revealed a gap between intention and behavior, where 80% of consumers had a positive willingness to pay for organic wine, but only 4% of consumers were all-organic wine buyers (i.e., purchase organic in 75-100% of cases). We found strong correlations between behavioral factors, confirming the validity of the proposed conceptual framework. We used supervised machine learning algorithms - random forest, decision tree, logit regression, and support vector machine - to estimate organic wine preferences. We then applied unsupervised machine learning algorithms - DBSCAN and HDBSCAN methods - to group consumers based on their similarity. Both classification and clustering emphasized the importance of attitudes, social norms, and hedonic goals, as well as purchasing and drinking frequency and the average price per bottle of wine. However, only clustering analysis revealed that emotions, impulsive tendencies, habits, and normative cues can prompt unplanned and spontaneous purchasing behavior and make consumers go against their beliefs. These findings have potential implications for industry and policymakers when promoting organic food and can contribute to the facilitation of demand-side solutions in the transition to sustainable agriculture.

5.1. Introduction

Since the introduction of chemicals in the 19th century, viticulture has significantly contributed to a wide range of environmental issues, particularly those related to land and water pollution. The heavy use of synthetic fertilizers, pesticides, and herbicides in intensive farming has already reduced the global insect species by 41%, and if this trend continues, in the next 100 years, none may be left (Sánchez-Bayo & Wyckhuys 2019). By excluding agrochemicals from vineyards, organic agriculture helps to preserve biodiversity and the overall quality of agroecosystems (Rugani et al. 2013). Organic agriculture contributes to the mitigation of the environmental burdens of wine production by excluding agrochemicals from vineyards (Provost & Pedneault 2016). Wines produced with organically grown grapes have a higher content of antioxidants (30%) (Vrček et al. 2011), lower content of orchatoxins (Gentile et al. 2016), and can be considered healthier choices compared to conventional wines. For a comprehensive discussion around the topic of organic wine quality and characteristics, we refer interested readers to Cravero (2019). Eliminating chemicals from land can enormously reduce the health risks to workers, their families, and communities (Costa, García-Lestón, et al. 2014).

Despite the recent growth in the rate of production of organic wines, especially in Europe, where organic vineyards constitute 9% of the harvested grape area (Willer & Lernoud 2019), the global organic wine market share is lower than 10% (Schäufele & Hamm 2018). Currently, less than 0.5% of grape production in Australia is organic, covering only 400,000 hectares of land (Wine Australia, 2017). Most certified organic wines are exported to Europe (78%; including Sweden and the United Kingdom (UK)) and the United States (12%). According to a recent report from Wine Australia (2019), the percentage of Australians who “sought to purchase any organic wine in the past six months” was approximately 20%. Even though there is a growing interest in organic wine in the global market, it remains a niche segment in the domestic market.

There is an ongoing debate about how to increase the organic wine market by promoting demand. Consumer choices and their willingness to pay (WTP) more for organic wines can support farmers in expanding organic vineyards (Taghikhah, Voinov, Shukla, Filatova, et al. 2020). Prior studies have reported that various factors are key drivers of consumers’ decisions in purchasing organic wine. Price (Panzone 2014), perceived that health and environmental benefits (Loose & Lockshin 2013), region of origin (Yang & Paladino 2015), superior taste and quality (Kim & Bonn 2015), as well as socio-demographics (such as age, gender, and income) (D'Amico, Di Vita & Monaco

2016) as among the most referenced factors in the literature. More recent studies have highlighted the relative importance of occasions (e.g., hosting friends, gift-giving) (Boncinelli et al. 2019), wine consumption and shopping frequency (Pomarici & Vecchio 2014), and drinking frequency (Pomarici, Amato & Vecchio 2016b) as predictors of consumer willingness to buy organic wine instead of conventional wine.

In the context of pro-environmental behavior, several researchers have highlighted a discrepancy between consumers' stated intentions and their actions, known as the intention-behavior gap. Even though consumers demonstrate WTP products with sustainability cues, and their intentions are high, these do not necessarily translate into actual behavior when it comes to purchasing decisions. With regard to organic wine, the bulk of the literature focuses on identifying determinants of WTP; yet, this is rarely differentiated from real purchasing behavior, as in the study by Schäufele & Hamm (2017), who confirmed the existence of inconsistencies between intentions to purchase organic wine and actual behavior among low-income consumers. This study found that price was the primary purchasing barrier. Poor quality and inferior taste are other reported reasons for avoiding organic purchases (Mann, Ferjani & Reissig 2012; Stolz & Schmid 2008).

In particular, impulsive and unplanned purchasing behaviors appear to interrupt the intention-behavior relationship. According to the literature on consumer behavior, affective factors, as well as cognitive and normative factors, can trigger behavior change (Russell et al. 2017). The non-cognitive factors, such as emotions, impulse tendencies, and personal goals, may underlie the failure to translate consumers' intentions into actions. Yet, to the best of our knowledge, there have been no quantitative studies to date that have investigated the relative importance of these factors as they relate to organic wine purchasing.

Moreover, quantitative research predicting consumers' intentions and behavior for purchasing organic wine has, to date, been dominated by statistical models. While these models can successfully reveal the relationship between variables, their predictive power and accuracy, as compared to machine learning (ML) algorithms, are low, especially when dealing with a high number of observations and attributes. Moreover, in contrast to statistical methods which need predefined mathematical models to estimate coefficients, ML methods do not need any mathematical representation to start with, as they adapt the parameters by learning from the data. ML methods can have multiple sub-models, each representing a subset of the dataset, whereas statistical methods fit one equation to the entire dataset. In classification problems, for example, statistical models such as logistic regression assume linearity of independent variables and log odds, whereas supervised learning can distinguish complex nonlinear patterns. Indeed, researchers have already applied distance-based methods such as k-means to identify different consumer clusters; however, density-based clustering methods have not yet been widely used. With a rare exception (Llobell, Vigneau & Qannari 2019), distance-based methods do not identify outliers in observational data and assign all the data points to the predetermined number of clusters (Güngör & Özmen 2017). Bzdok, Altman & Krzywinski (2018) has provided a more in-depth technical comparison between statistical and ML methods.

This study aimed to explore the determinants of heterogeneity in organic food purchasing intentions and behaviors. In order to identify the behavioral factors that drive purchasing decisions, we considered behavior change theories from psychology and developed a conceptual framework that integrates five relevant theories. We focused on organic wine as a case study and surveyed 1003 Australian consumers living in the City of Sydney. The collected data enabled us to quantitatively assess the impact of socio-demographics, shopping and drinking-related patterns, and behavioral factors on consumers' stated intentions and behavior for purchasing organic wine. The findings of this study reveal factors that cause the intention-behavior gap in pro-environmental food consumption. The novelty of this study lies in the examination of affective factors, including emotions, impulse tendencies, and personal goals, as well as cognitive factors, especially social norms, in the context of organic wine purchasing. It is the first specific study that has fully explored how this set of attributes affects preferences for organic wine. Moreover, our study advances the methodological principles of empirical wine studies by applying both supervised and unsupervised machine learning methods, providing new insights into different consumer segments and their decisions related to wine with sustainability characteristics.

We organize the remainder of this paper as follows: Section 5.2 explains the proposed theoretical framework used to develop the survey. Section 5.3 describes the methodological aspects, data collection tools, and the analysis process. Next, section 5.4 presents the results and Section 5.5 discusses them in the context of existing literature. The last section provides implications for practice and policy, and outlines potential avenues for future research.

5.2. Theoretical framework

Behavior change theories are widely applied to understand the internal, external, and interpersonal factors driving individual actions. To provide a more holistic perspective on pro-environmental purchasing behavior, we have referred to the principles of Stern's buying theory (Stern 1962), a well-known framework for classifying decisions as planned, impulsive, and unplanned. Planned purchasing behavior refers to time-consuming, information-searching, norm-dependent, semi-bounded rational decision making, whereas unplanned purchasing behavior refers to decisions that are driven by atmospheric store-related stimuli (e.g., promotions, posters) or habits (context-dependent stimuli) without any preliminary planning or actual need. Impulsive purchasing refers to rapid, spontaneous decisions driven by an individual's impulse tendency (i.e., a sudden, irresistible urge). Internal stimuli cause impulsiveness in response to mood swings, excitement, or unpleasant situations. Research shows that the use of sensory cues, such as the addition of scent or music, can influence consumers' emotions and impulse purchasing behavior (Helmefalk & Hultén 2017).

Similar to the study of Taghikhah, Voinov, et al. (2020b), we combined the strength of multiple relevant theories, including the theory of planned behavior (TPB) (Ajzen 1991), theory of interpersonal behavior (TIB) (Triandis 1977), impulsive buying theory (Stern 1962), alphabet theory (AT) (Zepeda & Deal 2009), and goal framing theory (GFT) (Lindenberg & Steg 2007), to understand the influence of cognitive and affective factors and explain differences in purchasing behavior. This allowed us to comprehensively explore the dynamics of purchasing decisions in different situations (e.g., shopping environment), understand the influence of context on the action (e.g., occasions), identify potentials to influence preferences (e.g., social media), and bridge the gap between intention and behavior. Figure 5.1 outlines the details of the theoretical foundation of this study.

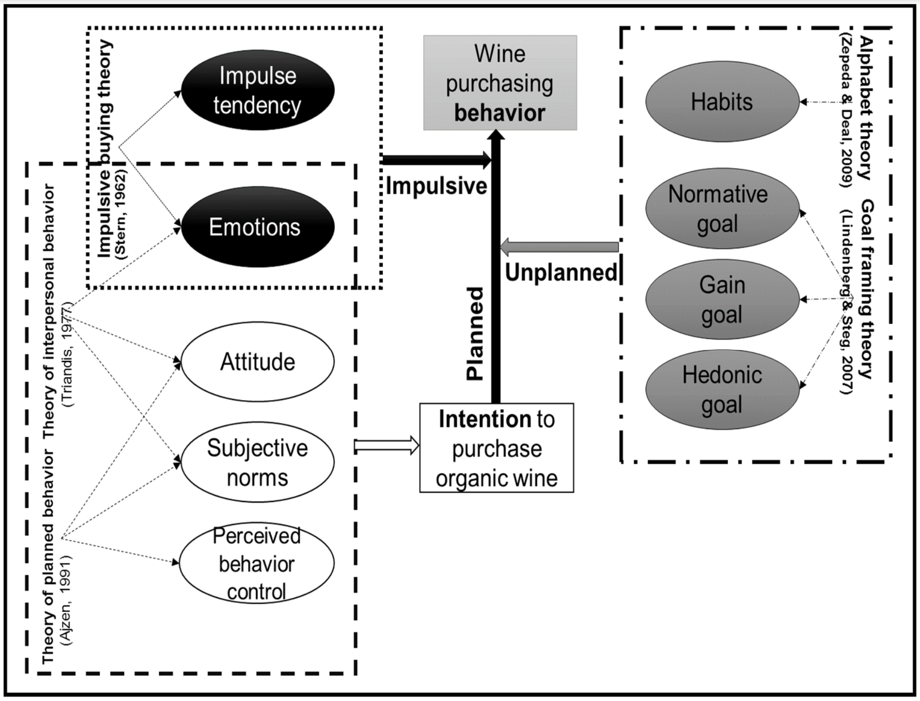


Figure 5.1. Conceptual model of the determinants of organic wine purchasing behavior.

Planned purchasing: TPB is the key theory for explaining planned pro-environmental behavior. In this theory, attitudes, perceived behavioral control (PBC), and subjective norms determine the intention, the main driver of behavior. Attitudes are an individual's opinions, beliefs, and tendencies towards a particular subject, while PBC refers to their ability and level of control to engage in certain behaviors. The perceived social expectations and peer-effect/pressure to adopt a behavior are represented by subjective norms. Consistent with Ajzen & Driver (1992), we conceptualized that a consumer's willingness to pay more for an item reflects their intention to perform the particular behavior[4]. TPB only focuses on the cognitive factors and largely disregards the impact of emotions, while TIB accounts for affect and emotional responses involved in decision making. According to this theory, cognitive and habitual responses, as well as emotional drivers, influence the rational deliberations of individuals when making decisions. Emotions are unconscious processes in the mind that prompt individual feelings and reactions to an object or an act as a trigger for a particular behavior (Forgas 1994). Emotions can be either positive or negative (neutral) (Lazarus, 1991). Prior literature has shown a relationship between positive emotions and greater intention to engage in a

[4] Notably, there is ongoing research on the relationship between WTP and intention for more complex one-time decisions with lasting consequences, such as environmental projects or renewable energy investments (refer to Bishop & Barber (2014) and Irfan et al. (2020)). For the purpose of our study, which focuses on weekly small-stake decisions, i.e., wine purchasing, we assume that an individual's WTP organic wine is a proxy for their intention to pursue the action.

certain behavior, such as personal use of the Internet at work (Moody & Siponen 2013) or energy-saving behavior (Webb et al. 2013).

***Impulsive purchasing*:** TIB argues that there is a direct relationship between affective factors and intentions. However, according to impulsive buying theory and affective events theory (Weiss & Beal 2005), under certain conditions, emotions can trigger a motivational impetus, which may further lead to impulsive behavior. Silvera, Lavack & Kropp (2008) and Dawson & Kim (2009) concluded that there is a direct relationship between an individual's affective state and impulse buying behavior if shopping uplifts their feelings and energizes them. Moreover, the likelihood of impulsive purchasing of experiential products, such as wine, is higher than the likelihood of purchasing other products because the emotional reactions and feelings after consumption of these experiential products are more important to consumers than their functionalities and attributes (Gutjar et al. 2015). Less is known about whether impulsive behavior is a response to positive or negative emotions during shopping.

***Unplanned purchasing*:** Despite its wide application, TPB lacks predictive power for automaticity in behavior, which is, in particular, critical for understanding low-involvement purchasing decisions (i.e., choices that pose a low risk and cost to consumers). Given that shopping, especially for food, is a repetitive, probably daily-weekly action, AT can supplement our theoretical framework by providing insight into habitual purchasing. This theory argues that besides values, beliefs, and norms of shopping and cooking, habits can influence the food choices of consumers. Habits are shaped by the repetition-reinforcement of behavioral patterns that require a low level of consideration. According to Gardner, Corbridge & McGowan (2015), the frequency of past behavior and automaticity of responses are the determinants of habits. Besides habits, GFT explains how environmental and atmospheric cues, such as sale promotional activities, POP posters, and retail environment design, can influence behavior and deviate it from intention. This well-known theory distinguishes three overarching goals to frame the unplanned behavior of an individual. These goals include the hedonic goal, to create a better feeling of enjoyment, the gain goal, to improve and protect personal resources, and the normative goal, to act appropriately for the group. Individuals pursue these goals at the same time inactively in the background. Once a goal gets activated by an environmental stimulus, a consumer's ability to act based on their intentions is reduced. For example, information/promotion campaigns in-store can activate individual normative goals and encourage the consumption of organic food. The presence of a relationship between PBC and behavior in previous studies (Sultan et al. 2020) highlights the relevance of gain goals and their influence on behavior.

The consideration of a combination of behavioral theories has allowed us to comprehensively explore the dynamics of purchasing decisions in different situations (e.g., shopping environment), to understand the influence of context on action (e.g., occasions), to identify potential influences on preferences (e.g., social media), and to bridge the gap between intention and behavior.

5.3. Methodology

Here, we present an overview of the methodology used to examine organic wine purchasing behavior. First, we designed a survey to collect data (Section 5.3.1). Second, the raw data were transformed into prepared data to be suitable for the ML algorithms. Then, correlation analysis was performed to identify the strength and direction of relationships between variables (Section 3.2.1). Finally, the ML algorithms were used to develop predictive models and detect homogeneous clusters of consumers (Sections 5.3.2.2 and 5.3.2.3). The data analysis was performed in Python. The following paragraphs briefly describe the survey and methods of analysis. Appendix 5.A presents more detail.

5.3.1. Data collection

According to the proposed theoretical framework in the previous section, we adopt different questions from the literature to design a questionnaire allowing us to measure the relationships between variables of interest. The questionnaire includes 7 sections consisting of 35 questions about (i) socio-demographic characteristics (10 questions), (ii) shopping and drinking-related style (7 questions), (iv) habits (1 question), (v) attitudes (3 questions), PBC (2 questions), (vi) social networks (3 questions), (vii) personal goals (4 questions), (viii) emotions, and (ix) impulse tendency (1 question). The questions for assessing habit, shopping patterns and emotions and impulsiveness are drawn from previous studies (e.g., Verplanken & Orbell (2003), Ogbeide (2013b), Watson, Clark & Tellegen (1988)). We use a multiple-question approach in assessing each question to improve the quality of results.

Following past research on consumer preferences for organic wine, we used WTP more (2 questions) as an indicator of intention to purchase organic wine. Moreover, the proportion of organic wine purchased relative to all wine purchases of a consumer (2 questions) was used as an indicator of organic wine purchasing behavior. We acknowledge that self-reported items do not always reflect the actual behavior in stated-preferences studies like surveys. However, the choice of what wine to buy is a regular decision, which stays in the memories of consumers. In this case, consumers were not thinking of a hypothetical decision when filling in our questionnaire; they were explicitly asked about a decision that is learnt and is practiced on an almost weekly basis. Our questionnaire explicitly asked respondents to remember whether they had purchased organic wine and what share of their actual past purchases was organic. Depending on the nature of the information collected, different types of questions/responses were used in the survey, such as multiple-choice (e.g., socio-demographics, shopping and drinking-related patterns), Likert-type scales (e.g., attitudes, emotions), and dichotomous questions (e.g., WTP and organic wine purchasing history). The details of the survey are available in Appendix 5.A1.

An expert panel consisting of two academic researchers and one practitioner reviewed and validated the questions. In September 2019, the online survey was conducted in 32 suburbs of the City of Sydney through Qualtrics online customer panel (https://www.qualtrics.com). The respondents were chosen randomly (from at least 18 years old respondents). We ran a one-stage pilot study with 50 respondents to test the consistency of responses and identify potential errors in questions. After screening out the incomplete responses, 1003 complete raw responses were included and used for analysis. This research has an ethics approval and is in line with the ethical guidelines and privacy requirements of the University of Technology Sydney, Ethic Number: HREC REF NO. ETH18-2483.

5.3.2. Methods of analysis

5.3.2.1. Data pre-processing and correlation analysis

For standardization, the variables containing discrete sequences of values, such as age, shopping frequency, shopping size, family size, etc. were normalized with the min-max normalization method to values between 0 and 1, in order to scale the differences in the ranges of the continuous variables. As our database contained categorical variables, a binary encoding procedure was used to convert these variables into binary variables. For example, we converted the variable “occupation,” which had five unique categories, into five binary variables (each presenting a unique category) and treated them each as a numeric variable. Our final data set included 1003 records and 89 variables. Then, we used descriptive statistics to understand the characteristics of respondents and derive the distribution of variables. Spearman's rank correlation was used to assess the strength and direction of the relationships between the nine latent variables representing behavioral factors. This allowed us to validate the proposed conceptual framework (refer to Section 5.2). We considered coefficients greater than +0.4 (and smaller than -0.4) to indicate a strong relationship, while those between 0.2 and 0.4 (-0.4 and -0.2) indicated a moderate correlation. The strength of a correlation depends on the context and sample size. According to Cohen (1992) and Cohen (2013) (often used in social sciences), coefficients around 0.3 and 0.5 represent moderate and strong correlations, respectively. However, in large sample sizes, a moderate correlation coefficient can be considered as significant as a strong correlation in a small sample, meaning that this relationship is unlikely to occur by chance.

5.3.2.2. Supervised learning: Classification

We used classification, the most commonly applied supervised learning approach, to estimate 6 classes of intentions and 5 classes of behavior for purchasing organic wine. The consumers who had no willingness to pay for organic wine were labelled as class (1) and those who had a willingness to pay for organic wine up to 10%, 20%, 30%, 40%, and 50% were labeled class (2), (3), (4), (5), and (6), respectively. Similarly, for predicting behavior, labels were assigned to consumers who purchased only conventional wine (class (1)), organic wine up to 25% (class (2)), organic wine between 25% and 50% (class (3)), organic wine between 50% and 75% (class (4)), and organic wine 75% or more (class (5)). We tested both parametric (logistic regression (LR)) and nonparametric (support vector machine (SVM)) classification algorithms (Cortes & Vapnik 1995), as well as the decision tree (DT) (Quinlan 1990) and random forest (RF) (Ho 1998) algorithms to identify the best performing method for classification of our data. Appendix A2 provides the details of the classification algorithms.

Parametric algorithms rely on the assumption that a linear combination of variables and coefficients can be fitted to a line, whereas nonparametric algorithms construct the model based on the similarities between patterns in data, without making any assumptions. While the selection of methods depends mainly on the characteristics of the data, higher flexibility and predictive power are generally expected for nonparametric algorithms. However, data requirement and overfitting issues should be carefully controlled for when using these algorithms. SVM finds the best prediction model using an optimization process to minimize the error function. DT uses conditional control statements in a flowchart-like structure to predict outcomes. Previous studies in different disciplines have reported better performance of ensemble methods like RF for classification, where multiple predictive models (in this case, trees) vote for the class assigned to a given sample so as to decrease biases and variances in predictions. The partitioning ratio for training and testing for each of these methods was set to 70% vs. 30%, respectively.

5.3.2.3. Unsupervised learning: Clustering

To identify hidden patterns or groups in our dataset, we used clustering, the most common unsupervised learning approach for exploratory data analysis. Density-based clustering algorithms such as DBSCAN can automatically detect the number of clusters and are suitable for cases where the clusters are not compact and well-separated (Ester et al. 1996). In contrast to ad-hoc methods that divide records based on one attribute, this method includes all attributes when computing the cohort outliers. Partitioning methods (e.g., K-means) and hierarchical clustering work by finding spherical-shaped clusters or convex clusters while DBSCAN identifies arbitrary-shaped clusters under fewer restrictions. However, since our database was highly dimensional and scattered, this algorithm failed to detect clusters of consumers with similar properties. Hence, we utilized its extension – HDBSCAN - designed to deal with high-dimensionality. HDBSCAN uses a technique to hierarchically represent every possible cluster generated by DBSCAN and extract a set of flat clusters (Campello, Moulavi & Sander 2013). We applied HDBSCAN on the pre-processed dataset with 89 dimensions from Section 3.2.1. As the algorithm failed to extract meaningful clusters when using all 89 dimensions (the noise was 70%), we further used the principal component analysis (PCA) method to gradually reduce the dataset dimensions, minimize the clustering noise, and increase the density of resulting clusters. PCA identified six dimensions where the clustering noise was the lowest and the density of resulting clusters was the highest. Further, relying on the HDBSCAN recommendations for selecting parameters, we used the approach proposed by Rahmah & Sitanggang (2016) to tune its hyper-parameters. Appendix 5.A3 provides details of HDBSCAN and the settings for its hyper-parameters.

5.4. Results

We applied a set of analytical techniques to examine the factors that influence the organic wine purchasing of households. First, descriptive analysis was performed to examine the relevant demographic, cognitive, and behavioral factors (Section 5.4.1). Second, correlation analysis was used to quantitatively assess the strength of all factors in the wine-related decision-making process (Section 5.4.2). Third, supervised ML was used to learn the prediction model and estimate the likelihood of intention and behavior for purchasing organic wine (Section 5.4.3). Fourth, unsupervised ML was used to find the unknown wine purchasing patterns in the survey data (Section 5.4.4).

5.4.1. Descriptive analysis

Table 5.1 compares the socio-demographic characteristics of the City of Sydney (LGA) population (collected from the Australian Bureau of Statistics (ABS) - 2016 census) with the collected sample (own survey - 2019). The results indicated that, except for educational level, the sample is representative of the population, which is in line with Qualtrics's policy assuring the representativeness of their survey panels. While our sample is representative of individuals with a graduate degree, it over-represents people with postgraduate education and underestimates individuals with school education, as compared to the 2016 census. The reasons for this may include the housing boom and rapid urban relocation dynamics in Sydney bringing more highly-educated specialists to the CBD in 2019 compared to 2016. Further, the online format of data collection may have been appealing to more educated people. Nevertheless, as discussed in Section 5.4.2 below, education was only moderately correlated with intention and behavior, and we argue that the possible education gap between our sample and the local population should not affect the main conclusions of the study.

Table 5.1. Socioeconomic distribution in the City of Sydney (LGA) and the survey sample.

Factors	City of Sydney LGA	Survey sample
Total number of households	85,423	1,003
Female population (%)	47%	41%
Median age group	30-40 years old	36-45 years old
Median total income	AU$75,001 to AU$150,000	AU$75,001 to AU$150,001
Average household size	2	2
Education level		
● Postgraduate Degree levels (%)	17.9%	51.1%
● Graduate Degree level (%)	39.9%	36.8%
● School education level (%)	42.2%	12.1%

Analysis of the socio-demographic characteristics of the survey respondents showed that (1) gender was balanced and can adequately reflect differences between males and females, (2) the majority of consumers were highly educated and worked full-time in management and engineering occupations, (3) the income level of more than two-thirds of the consumers was between AU$ 75 and AU$ 250 thousand, which was higher than the average Australian income and (4) about half of the respondents were single or in a couple.

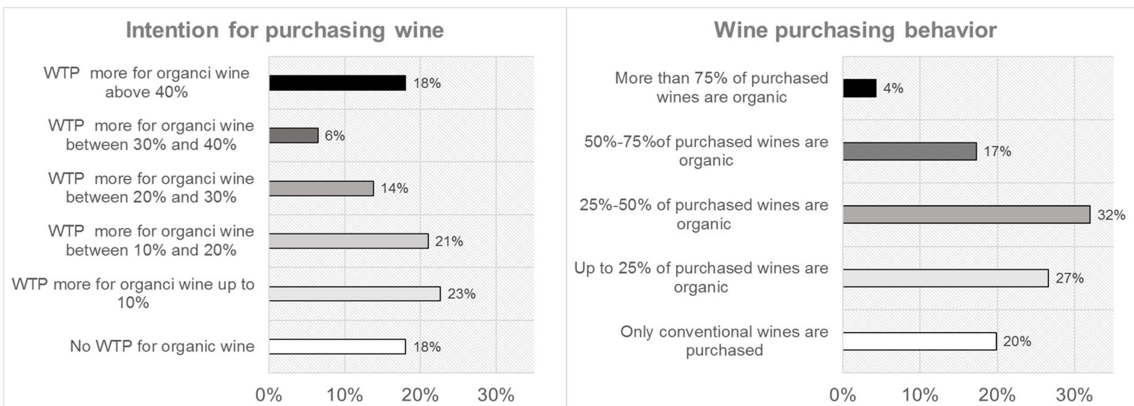
Regarding consumers' patterns of wine purchasing and consumption, the results indicated that the majority of respondents surveyed visited wine shops more than once a week and purchased more than five wine bottles per month. More than 70% of consumers purchased the same brand of wine quite often and reported drinking wine 2 to 5 times a week.

Table 5.2 presents the summary statistics for the behavioral factors related to purchasing behavior. All factors were measured on a Likert scale ranging from 1–5 and were standardized between 0 (strongly disagree) and 1 (strongly agree) as explained in Section 5.3.2.1. The results showed that, on average, consumers have positive attitudes towards organic wine and positive emotions during shopping. Most consumers reported high habitual and low impulsive purchasing. Consumers reported a distinction between organic and conventional wine and reportedly like the taste of organic. The advice of staff, choice of other people at the shop, and social media were not significant predictors of wine choice. While wine availability was important to them, they indicated no concern for price.

Table 5.2. Importance of behavioral factors among survey respondents.

Behavioral factors	Sub factors	Measures	Average	Standard deviation
Cognitive	*Attitude*	Trust on organic wine	0.74	(0.19)
		Environmental knowledge of organic wine	0.73	(0.17)
		Health knowledge of organic wine	0.72	(0.16)
	Perceived Behavioral Control	Importance of wine price	0.37	(0.35)
		Importance of wine availability	0.56	(0.28)
	Habit	Automaticity of purchasing	0.69	(0.21)
	Hedonic goals	Taste	0.85	(0.29)
		Difference and distinction	0.78	(0.36)
		Likeness	0.72	(0.39)
	Gain goals	Change of price at the shop (switch preference)	0.42	(0.35)
		Change of availability at the shop (switch preference)	0.32	(0.37)
Normative	*Social norms*	Frequency of socializing about wine	0.57	(0.3)
		Purchasing wine for occasions	0.65	(0.47)
		Advice of family and friends	0.75	(0.15)
	Normative goals	Staff and others at shop	0.33	(0.23)
		Social media	0.17	(0.26)
Affective	*Emotions*	Positive emotions	0.75	(0.25)
	Spontaneous urge	Impulse tendency	0.29	(0.3)

Figure 5.2 presents the distribution of intention (a) and behavior (b) for purchasing organic wine among our survey respondents. We considered WTP more for organic wine as an indicator of individual intention and the proportion of purchased organic wine in the shopping basket as an indicator of actual behavior. The analysis showed that more than 80% of consumers had a positive intention for purchasing organic wine. Interestingly, only 4% of consumers were exclusively-organic wine buyers (i.e., purchase organic in 75-100% of cases) with an additional 17% of consumers indicating they are frequent organic wine buyers (i.e., between 50-75% of their wine shopping basket is organic). 60% of respondents indicated that less than 50% of their wine shopping basket is organic while 20% had never purchased organic wine before. These results highlight a significant gap between intention and behavior in organic wine purchasing.



(a) Intention to purchase organic wine (b) Wine purchasing behavior

Figure 5.2. Percentages of survey respondents who have positive intentions to purchase organic wine (a) and their wine purchasing behavior (b).

5.4.2. Correlation analysis

Table 5.3 presents the correlation matrix for the nine latent variables representing behavioral factors, including attitudes, PBC, social norms, emotions, habits, impulse tendencies, hedonic, gain, and normative goals. Overall, attitudes and emotions were most strongly correlated with the other variables, while the weakest correlations were between gain goals and the other variables.

Table 5.3. Triangular matrix of correlations among latent constructs of behavior (bold, underlined values represent strong correlations and italic values show moderate correlations)

Variables		Attitude	PBC	Hedonic goal	Gain goal	Habits	Social norms	Normative goal	Emotions	Impulse tendency
Cognitive	Attitude	_								
	PBC	*0.31*	_							
	Hedonic goal	**0.48**	*0.23*	_						
	Gain goal	*-0.24*	-0.1	*-0.22*	_					
	Habits	**0.59**	*0.23*	**0.42**	-0.18	_				
Normative	Social norms	**0.47**	*0.24*	**0.46**	-0.16	**0.49**	_			
	Normative goal	**0.48**	0.18	**0.36**	-0.13	**0.52**	**0.5**	_		
Affective	Emotions	**0.56**	*0.24*	**0.45**	*-0.2*	**0.61**	**0.49**	**0.54**	_	
	Impulse tendency	**-0.42**	-0.18	*-0.24*	0.13	**-0.46**	*-0.35*	**-0.45**	**-0.51**	_
	Variables	**Cognitive**					**Normative**		**Affective**	

Table 5.4. Correlations between intention and behavior for purchasing organic wine and other variables, where strong correlations are bold and underlined and moderate correlations are in italics.

			Organic purchasing intention	Organic purchasing behavior
Socio-demographic factors		Gender	*-0.28*	*-0.33*
		Retired	*0.31*	*0.38*
		Household size	*0.2*	*0.32*
		Average household education	*0.37*	*0.34*
		Average household income level	*0.28*	*0.31*
Shopping and drinking-related patterns		Average wine shopping size per month	**0.43**	**0.51**
		Wine drinking frequency	**0.45**	**0.53**
		Wine purchasing frequency	**0.5**	**0.64**
		Time spent in wine shops	**0.42**	**0.45**
		Loyal to certain brand of wine	*0.26*	*0.28*
		Average price paid for wine	**0.54**	**0.6**
		Maximum price willing to pay for wine	*0.26*	*0.22*
Behavioral factors	Cognitive	Like organic wine	**0.49**	**0.61**
		Distinction between organic and conventional wine	**0.47**	**0.51**
		Perceive organic wine tastier	**0.48**	**0.56**
		Habitual wine purchasing	**0.45**	**0.53**
		Environment belief for organic wine	**0.57**	**0.5**
		Health belief for organic wine	**0.53**	**0.51**
		Trust in organic wine	**0.59**	**0.56**
		Price importance for purchasing wine	*0.32*	*0.29*
		If price increases, cheaper substitution	*-0.27*	*-0.2*
		If price increases, no substitution	*-0.32*	*-0.19*
		If price increase, loyalty	**0.51**	*0.33*
		If unavailable, no substitution	*0.28*	*0.34*
		If unavailable, cheaper substitution	*-0.2*	*-0.22*
		If unavailable, expensive substitution	-0.15	*-0.2*
	Normative	Influence of family	*0.37*	**0.4**
		Influence of friends	*0.33*	*0.35*
		Influence of other shopper	*0.39*	**0.46**
		Influence of social media	**0.46**	**0.53**
		Frequency of talking about wine when socializing	**0.41**	**0.45**
		Organic wine for special occasion	**0.51**	**0.66**
	Affective	Positive emotions during shopping	**0.46**	**0.63**
		Impulsive/spontaneous shopping	*-0.31*	*-0.29*

Attitude was strongly positively correlated with social norms, emotions, hedonic goals, and habits. Additionally, it was strongly and moderately negatively correlated with impulse tendency and gain goals, respectively. The amplifying effect of emotions on attitudes toward change is well-discussed in the study by Vulpe & Dafinoiu (2011). PBC showed no strong relationship with the other latent variables and was only moderately positively correlated with social norms, positive emotions, habits, and hedonic goals. Social norms was positively related to emotions, habits, hedonic, and normative goals, while negatively to impulse tendency. The correlations between emotions and habits, hedonic, and normative goals were strongly positive, while that with impulse tendency was strongly negative. We found that habits was strongly positively correlated with hedonic and normative goals. As expected, its correlation with impulse tendency was strongly negative, which, in a way, distinguishes automaticity in behavior from impulsiveness. In general, customers with negative attitudes and feelings, and who are against norms and habits, tend to purchase wine more impulsively. The positive and strong relationship between hedonic and normative goals shows the influence of other people's opinions on the perceived taste of food. Studies of products such as bread (Inaba et al. 2018) and chocolate (Boothby, Clark & Bargh 2014) have revealed the role of co-eating in changing the perceived taste of participants. Finally, consumers who engage in habitual and norm-confirming wine purchasing seem to enjoy shopping and have more positive attitudes towards organic products.

The correlation between intention to purchase organic wine and behavior was substantial (0.61). We then calculated the correlation matrix for the relationships between wine purchasing intentions and behavior and all the database variables. Table 5.4 shows that both intention and behavior were strongly and positively correlated with hedonic goals (likeness, taste, distinction), attitudes (health belief, environmental belief, and trust), habits, emotions, social norms (special occasion and socializing), and shopping and drinking-related patterns (wine drinking frequency, purchasing frequency, shopping size, time spent at wine shop, and average price paid for wine). On the other hand, demographics, including gender, family size, education, and income, were moderately correlated with intention and behavior. Moreover, the relationships between impulse tendency, wine substitution (if the products are unavailable), and organic wine purchasing intention and behavior were negative. Appendix 5.B presents the details of the correlation analysis for all database variables.

5.4.3. Supervised machine learning: Classification analysis

We compared the performance of SVM, LR, DT, and RF in predicting consumers' intentions (5.4.3.1) and behavior (5.4.3.2) for purchasing organic wine. The comparison helped us to select the best performing algorithm in our survey data.

5.4.3.1. Predicting consumers' intentions to purchase organic wine

We assessed the accuracy of the predictive models of the different algorithms for estimating the probability of organic purchasing intention. As presented in Figure 5.3, all the predictive models showed the highest accuracy in predicting the likelihood that a consumer is "not willing to pay" (a premium), "willing to pay 10% and 20% more", "willing to pay 30% and 40% more", and "willing to pay 50% and higher more." Moreover, in all the presented experiments, RF outperformed the other algorithms (DT, SVM, and LR), while LR had the lowest accuracy (Figure 5.3). Apparently, non-parametric algorithms are better able to handle homogeneity amongst classes, resulting in higher accuracy and higher efficiency in processing complex and highly dimensional datasets. Appendix 5.C1 provides the details of the analyses and the decision tree resulted from RF model for predicting 4 classes.

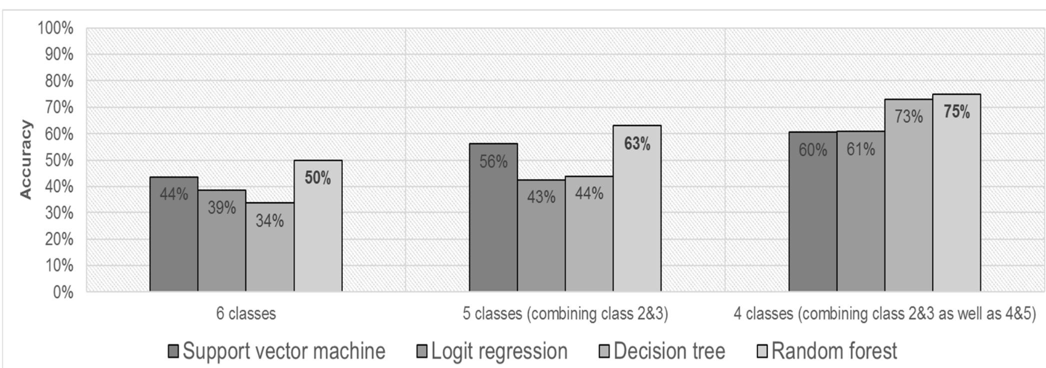


Figure 5.3. Comparing the performance of the algorithms (i.e., support vector machine (SVM), logit regression (LR), decision tree (DT), random forest (RF)) in predicting consumers' intentions across three models.

Table 5.5. The importance of factors in predicting intention according to random forest analysis (variables repeated in the three models are indicated with *; the most important factor and numbers are underlined and bolded).

Factors		Variables used in RF model	Importance in 6 class model	Importance in 5 class model	Importance in 4 class model
Behavioral factors	Cognitive	**Like** organic wine*	0.02	0.03	0.02
		Perceive organic wine **tastier**	-	0.03	0.03
		Trust in organic wine*	***0.05***	***0.05***	***0.06***
		Environmental belief about organic wine*	***0.05***	***0.05***	0.05
		Health belief about organic wine	-	0.03	0.03
		Habitual wine purchasing*	0.03	0.03	0.03
		Distinction between organic and conventional wine	0.02	-	0.02
		Wine price importance	0.02	-	0.02
		Wine availability importance	-	-	0.02
	Normative	Talking about wine when **socializing***	0.02	0.03	0.03
		Organic wine for **special occasion**	-	-	0.02
		Family and friend influence	0.02	-	0.02
		Other shoppers influence	0.02	-	0.02
		Wine shop **staff** influence	0.02	0.03	-
		Social media influence on wine choice	-	-	0.02
	Affective	Positive **emotions***	0.03	0.04	0.05
		Impulsive shopping tendencies*	0.03	0.03	0.02
Shopping and drinking-related patterns		**Average price** paid for wine*	***0.05***	0.04	***0.06***
		Time spent in wine shop *	0.02	0.03	0.02
		Wine **purchasing frequency***	0.03	0.04	0.04
		Average wine **purchasing size***	0.02	0.03	0.04
		Wine **drinking frequency***	0.03	0.03	0.03
		Frequency of comparing different wine **prices**	0.02	-	0.02
		Loyalty to a certain brand	-	-	0.02
Socio-demographic factors		Household average **income**	0.02	-	0.02
		Household highest **education**	-	-	0.03
		Age	0.02	-	0.02
		Household size	0.02	-	0.02
		Gender	-	-	0.02

Apart from delivering predictive models, RF provides a deeper understanding and useful information about the relative importance of different variables affecting overall accuracy. Table 5.5 presents the importance weights of variables for predicting consumers' intentions across three models. We found that for organic wine intention, consumers' trust in organic wine had the highest predictive power, followed by environmental belief in organic wine and the average price paid for a bottle of wine (importance weights varied between 0.04 and 0.06 in the three models). On the contrary, factors such as age, loyalty, wine availability, and special occasions were of the lowest importance (importance weight of 0.02, only in one model). Besides trust in organic farming, environmental belief about organic wine, positive emotions, higher payment for wines, more hedonic motivations, habitual purchasing, and high-frequency wine drinking and purchasing were associated with greater intention to purchase organic wine.

5.4.3.2. Predicting consumers' likelihood of purchasing organic wine

We assessed the accuracy of the predictive models of the different algorithms for estimating the probability of purchasing organic wine. Similar to intention prediction, RF outperformed the other algorithms, but SVM had the worst performance. Moreover, DT and LR demonstrated comparable performance, except in predicting 3 classes, where DT outperformed (Figure 5.4). Appendix 5.C2 provides the details of the analyses and the decision tree resulted from RF model for predicting 3 classes.

We then measured the importance of all predictor variables and kept the significant variables in the model. However, there was not full agreement among models about the importance of the variables. For example, the 5-class model indicated that positive emotions and the average price paid for wine had the strongest influence, while the 4-class model indicated that special occasions was the most important factor (for more details, please refer to Appendix 5.C3). Thus, we tested the performance of the models when the intention variable was included in our analysis as another predictive factor.

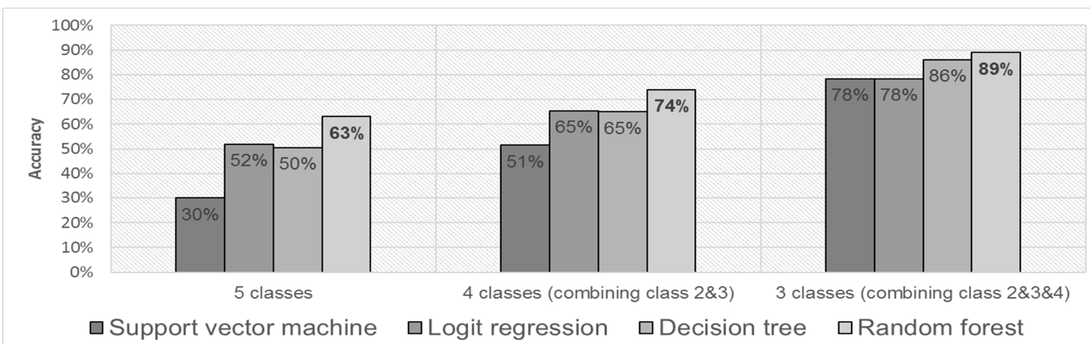


Figure 5.4. Comparing the performance of the different algorithms (i.e., support vector machine (SVM), logit regression (LR), decision tree (DT), random forest (RF)) in predicting wine purchasing behavior.

Regarding the model accuracy, the inclusion of intention led to no improvements. However, we found that the average price paid for wine was consistently the most important factor in predicting organic wine behavior, as shown in Table 5.6 (importance weights between 0.07 and 0.1). Shopping and drinking-related patterns played a similar role in predictor behavior as observed in relation to intention. Consumers who more frequently purchased more bottles of wine, reported drinking more often, and spent more time at the shops were more likely to purchase organic wine. Behavioral factors, including cognitive (i.e., intention, attitude, habits), normative (i.e., purchase occasions, social media), and affective (only emotions) were other emergent proxies for organic wine purchasing behavior. Finally, socio-demographic factors appeared to be unimportant in predicting purchasing decisions.

Table 5.6. The importance of factors in organic wine purchasing behavior according to random forest analysis (variables repeated in three models are indicated with * and the most important factor is underlined).

Factors		Variables used in RF model	Importance in 5 class model	Importance in 4 class model	Importance in 3 class model
Behavioral factors	Cognitive	**Intention** for purchasing wine*	0.05	0.05	0.06
		Trust organic wine*	0.03	0.02	0.02
		Health belief about organic wine*	0.03	0.03	0.02
		Environmental belief about organic wine*	0.03	0.02	0.02
		Habitual wine purchasing*	0.03	0.04	0.03
		Like organic wine*	0.03	0.03	0.07
		Distinction between organic and conventional wine	-	-	0.05
	Normative	Influence of **social media***	0.03	0.04	0.04
		Organic wine for **special occasion***	0.04	0.03	0.08
		Influence of **other shoppers**	0.02	-	-
	Affective	Positive **emotions***	0.04	0.04	0.03
Shopping and drinking-related patterns		***<u>Average price paid for wine</u>****	***<u>0.07</u>***	***<u>0.10</u>***	***<u>0.09</u>***
		Wine **purchasing frequency***	0.04	0.04	0.06
		Time spent in wine shop*	0.03	0.06	0.04
		Wine **drinking frequency***	0.03	0.03	0.04
		Average wine **purchasing size***	0.03	0.04	0.03
Socio-demographic factors		**Income**	0.02	-	-

5.4.4. Unsupervised machine learning: Cluster analysis

The HDBSCAN method identified three hidden heterogeneous clusters of consumers (Figure 5.5). The size of each cluster varied from a minimum of 63 (7%) for cluster 1 to a maximum of 326 (33%) and 327 (33%) for clusters 2 and 3, with 29% of data labelled as noise. Although this percentage of noise may seem high, the literature (Chen et al. (2018); Maurus & Plant (2016) indicates that such a level of noise in the data is common in density-based algorithm studies. We compared the characteristics of clusters in terms of the different variables. As reported in Figure 5.6, clusters exhibited significant differences in terms of demographics (e.g., income, education), behavioral factors (e.g., attitudes, habits, emotions), and shopping and drinking-related patterns (e.g., wine drinking, purchasing frequency). We labeled these clusters as non-organic (Section 5.4.4.1), occasional organic (Section 5.4.4.2), and organic segments (Section 5.4.4.3).

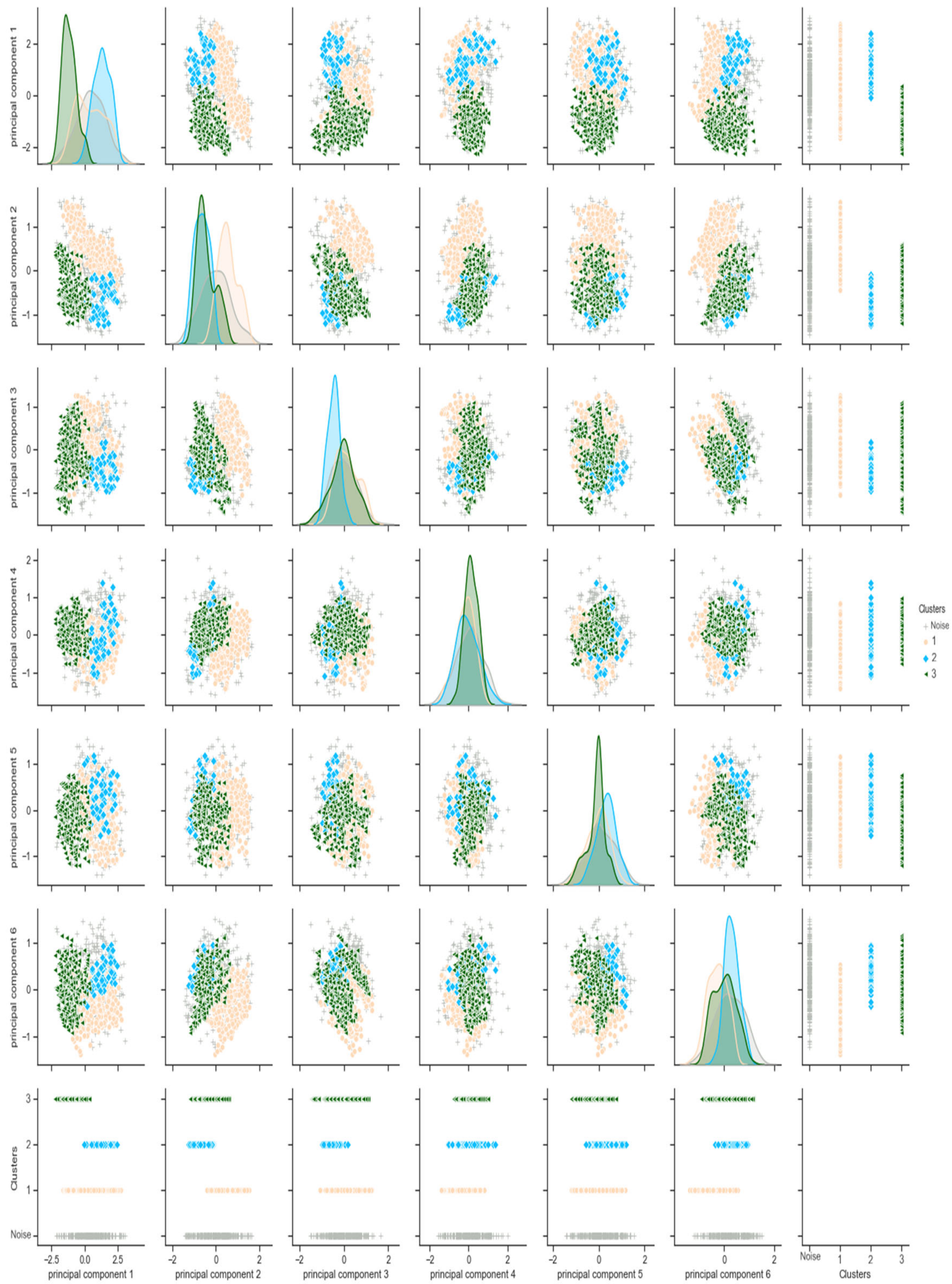


Figure 5.5. HDBSCAN results with three clusters (1, 2, and 3) in six dimensions. Clusters 1, 2, and 3 are represented by circles, diamonds, and triangles, respectively. Cluster 0 is noise.

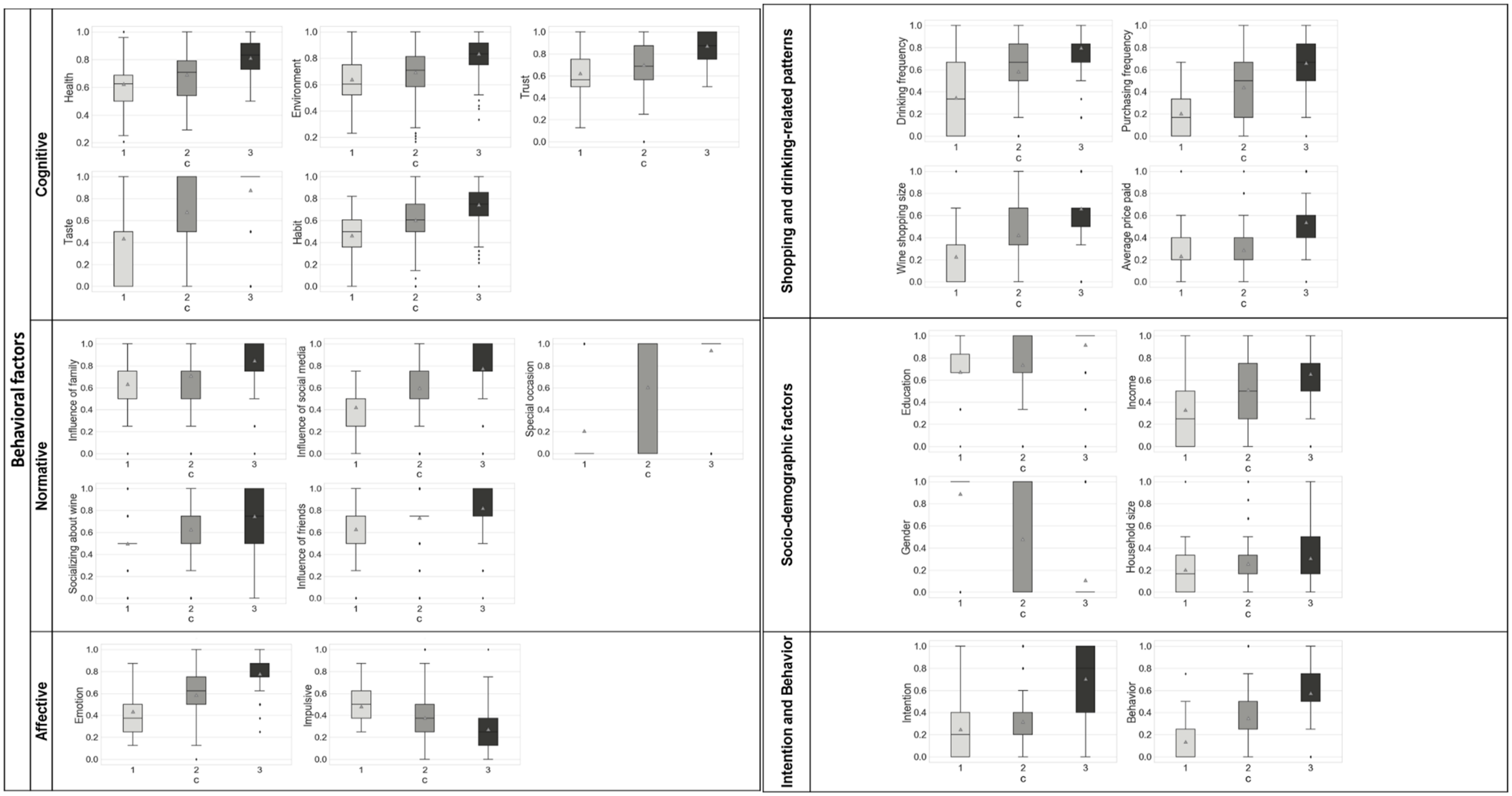


Figure 5.6. Variables according to which the three clusters (1, 2, and 3) are segregated. Special occasion (no=0, yes=1) and Gender are binary variables (male=0, female=1). The clusters are clearly different according to most of variables, while there are some overlaps in others.

5.4.4.1. Non-organic segment: Impulsive behavior

Cluster 1, the non-organic segment, mainly represents conventional wine consumers. They reported the lowest wine consumption and usually purchased items spontaneously. The gap between their higher intention (WTP 20% more) and lower organic purchasing behavior (organic wine purchasing less than 25%) is well-explained by high impulsiveness. The wine drinking and shopping frequency of this cluster were the lowest. Conventional wine consumers expressed negative feelings during shopping. They did not like the taste of organic over conventional wine or reported no distinction between the two. Although they reported that health and environmental impacts are relatively important decision factors, they were less convinced that organic products have health and environmental benefits and did not trust them. Social norms influenced the wine purchasing decisions of these consumers very slightly. They stated that, in case of an increase in the price of their favorite wine, they would look for a cheaper substitute. In fact, they reported less loyalty to a certain brand of wine compared to other clusters. Regarding socio-demographic factors, consumers in this cluster were mainly poorly educated, lower-income women who had small-size households.

5.4.4.2. Occasional organic segment: Planned behavior

Cluster 2, the occasional organic segment, represents the bulk of the consumers with the highest potential for organic wine adoption. The intentions and behavior of these consumers were well aligned (WTP 10-20% more for organic and purchasing 25-50% of wines organic), indicating planned wine purchasing behavior. For this cluster, price was by far the main driver preventing organic wine purchasing decisions in this cluster: when the price of organic wine increases, they are unlikely to purchase it anymore (no substitution). Although the average price paid for wine in this cluster was similar to cluster 1, organic wine was mostly purchased for special occasions. In general, these consumers believed in the environmental and health benefits of organic wine consumption, but due to its high price, they only purchased it for celebrations or as a gift. Compared to conventional consumers, occasional organic consumers had relatively higher education, income, family size, brand loyalty, and interest in drinking organic wine and were less prone to impulsive wine shopping.

5.4.4.3. Organic segment: Unplanned behavior

Consumers in cluster 3, the organic segment, were mainly men with the highest education and highest income levels, living in big families. The average share of organic wine in their basket was more than 50%, higher than their reported intention (WTP varied between 20-50%). They based their choice primarily on normative goals and habits. On the one hand, the influence of family and friends and other shoppers' choices on their wine purchasing decisions was the highest. They looked for more information about different wines from social media and sought the advice of others when selecting wine. On the other hand, they were generally happy during shopping and tended to buy items habitually. Thus, the characteristics of this class are representative of unplanned wine purchasing behavior. Consumers in this cluster are strongly concerned with the health and environmental impacts of their food choices. Changes in the price of wine have a low impact on their demand, and their average price acceptance is at a maximum. In other words, the price elasticity of this cluster is low, and if the prices of products increase, consumers will continue to purchase at higher prices.

5.5. Discussion

Our findings confirm the presence of planned, unplanned, and impulsive behaviors when shopping for wine. The following discussion of the results highlights a set of similar and distinct behavioral, drinking style, and socio-demographic factors that can explain consumers' wine preferences.

Regarding the cognitive factors, RF models showed that trust adds substantially to the prediction of intentions. Similarly, Kim and Bonn (2015) reported that trust in the winery is the main factor influencing intentions to purchase organic wine. In line with the study of D'Amico, Di Vita, and Monaco (2016), the present study found that environmental consciousness and curiosity were associated with consumer WTP a premium for organic wines. When it comes to purchasing behavior, health attributes were found to be an important motivator for purchasing organic wine, a finding which is consistent with the studies of Mann, Ferjani & Reissig (2012) and Bonn, Cronin Jr & Cho (2016). Having said that, we found that consumers in cluster 2 mainly purchase conventional wine, despite their positive attitudes towards the health and environmental beliefs associated with organic products. Hence, we could not confirm that attitudes strongly predict behavior. Prior studies have reported contradictory results regarding the importance of taste on organic wine purchasing behavior (Mann, Ferjani & Reissig 2012).

Nevertheless, our classification and clustering analyses were consistent with the study by Kim & Bonn (2015), in which American consumers reported taste as an important factor in their wine choice.

The influence of habits on more WTP for organic wine has not been sufficiently explained by the results of other studies in this context. Most wine-related studies define habits as the repetition of behavior as assessed by frequencies of shopping and drinking (e.g., Pomarici, Amato & Vecchio (2016a) Vecchio (2013), whereas, here, we considered habit as cognitively effortless and automatically initiated behavior, as assessed by the automaticity-specific index (Gardner et al. 2012). Our findings highlighted the importance of habitual purchasing in promoting both organic wine purchasing intention and behavior. However, contrary to our expectations, habits did not override intention in directing behavior, and intentions remained significantly and equally predictive of behavior in all models: consumers choose wine mindfully rather than habitually. Gardner, Corbridge & McGowan (2015) referred to the temporal self-regulation theory to explain similar observations in terms of unhealthy snacking behavior, where strong self-control inhibits the habit. Similar to other organic wine studies (e.g., Brugarolas et al., 2013; Pagliarini, Laureati & Gaeta (2013), we found that WTP more for organic wine (intention) strongly influenced organic wine behavior. The classification results showed that, on average, consumers with higher WTP for organic wine also had a higher probability of buying it. However, our cluster analysis detected clusters of consumers with relatively higher intention and lower behavior for organic wine (clusters 1 and 3). A similar gap between intention and behavior for organic wine has been described by Schäufele & Hamm (2018), who found that attitude and price are the barriers to organic wine adoption.

Regarding normative factors, we found that more normative support, as provided by social media and purchasing occasions, was relevant in determining consumers' organic wine purchasing behavior. This result highlights the influence of wine reviews and recommendation systems on consumers' choices. It also highlights new potentials and opportunities for social media to assist businesses and industries to influence consumers' preferences. Szolnoki et al. (2018) and Dolan & Goodman (2017) both recently investigated the application of social media for promoting wine. Moreover, in line with the study of Boncinelli et al. (2019), in the current study, consumers valued organic wine more for special occasions rather than personal consumption. Concerning the clustering results, this statement stands true for 33% of consumers (occasional segment), while for the rest, it might not be the case, as occasions only partially influenced their wine purchasing decisions.

Regarding the affective factors, our findings demonstrate that happier, positive, and optimistic consumers are more likely to pay more for organic wine. Consistent with the study by Danner et al. (2016), positive and negative emotions were predictive of WTP more for organic wine. The influence of impulsive tendencies on organic wine purchasing decisions was more prevalent in the cluster analysis. On the one hand, impulsiveness caused by negative emotions may prompt spontaneous behavior that may, in turn, drive the consumer towards purchasing more conventional wine. On the other hand, unplanned decisions triggered by habits and normative cues may lead to higher organic purchasing if a consumer experiences positive emotions. Therefore, we can relate the effects of emotions to either impulsive or habitual behavior. Despite the importance of impulsiveness in predicting wine purchasing decisions, we only found one study, by Feldmann & Hamm (2015), that has highlighted the influence of spontaneous purchase situations.

Regarding shopping and drinking-related patterns, the classification method indicated that the average price paid for wine was the strongest predictor and the source of heterogeneity in the average behaviors of consumers. A higher price acceptance increases the likelihood that a consumer is more willing to pay a premium for organic wine. In the literature, the findings are mixed regarding the importance of price for buying organic wine; however, our results are in line with the studies of Schäufele & Hamm (2018) and Di Vita et al. (2019) who reported that, for the majority of consumers, price is the pivotal driver of wine choices. Another interesting result of the current study is that while consumers state they generally pay little attention to wine prices (about 70% of respondents), they actually base their organic wine purchasing decisions primarily on ‘price’. While wine prices were considered to be the best predictor of organic wine purchasing behavior according to the RF model, the HDBSCAN model identified clusters that have equal average price acceptance, but the proportion of organic wine in their shopping baskets differed (refer to Figure 6, where organic wine in the shopping basket was less than 25% for cluster 1 and between 25-50% for cluster 2). The type of consumer behavior can explain this inconsistency in results; the wine purchasing decisions of cluster 2 consumers are more planned, whereas the decisions of cluster 1 consumers are more impulsive. The conventional segment consumers may change their preference for organic consumption if they experience positive emotions (like joy and contentment) during shopping and practice more planned buying. Interestingly, for the organic food segment, cluster 3, food price was the most important wine attribute, and that is why their high WTP more for organic wine (between 20% and 50%) cannot lead to full adoption of organic wine. The present findings seem to support the findings of Janssen, Schäufele

& Zander (2020), where both conventional and organic food consumers reported that price was the most important attribute when making purchasing decisions.

Apart from the average price paid, variables such as the duration of shopping, average purchasing size, and the frequency of purchasing and drinking wine were found to be strong predictors of both intentions and behavior. It seems that consumers who spend a long time in the shop searching for products are likely to be willing to pay more for organic wine. Further, the more wines purchased per month, the higher the likelihood of intentions and behavior for purchasing organic wine. In line with previous studies, such as those by Pomarici and Vecchio (2014) and Vecchio (2013), higher frequencies of consuming and purchasing wine are related to a higher WTP more for organic wine.

Regarding socio-demographics, in agreement with the study by Zepeda and Deal (2009), the classification results indicated that socio-demographic factors have the lowest predictive power and are poor proxies for intention and behavior models. However, our clustering results revealed significant differences in income, education, household size, and gender between organic and conventional wine consumers.

This study has a number of limitations that should be noted and the results highlight several potential directions for future research. Firstly, the reliance on self-reported behavior rather than conducting observational experiments is a limitation. Survey respondents are prone to social desirability bias in reporting their intention for organic products, and their behavior can only be interpreted as a reported preference; it is not their real behavior. Thus, the findings of this study are of an experimental nature. One possible future direction is to use real market transactions presented in household panel data to conduct unbiased market studies and provide more realistic, robust results. Another limitation of this study is relevant to the geographical constraints of the sample and the generalizability of the results. Our data were collected from one region of a major city in Australia and there is a possibility that the results are more closely aligned to the perspectives of these particular residents. Thus, the results cannot be generalized to the entire population. Future research may choose to broaden the participant recruitment process or conduct a comparative study on the differences and similarities between organic wine preferences of Australians across different states and other populations. Finally, the impact of packaging, region of origin, grape variety, and other extrinsic characteristics on organic wine purchasing can be explored in future research.

5.6. Conclusions

Our findings have important implications for both theory and practice. From a theoretical perspective, they underscore the importance of considering impulsive and unplanned, as well as planned behavior, in understanding food purchasing. We argue that organic purchasing decisions result from an interplay between these factors, as explained by different social theories. Relying only on planned behaviors and disregarding the presence of interruptive factors between intention and behavior means that we are unlikely to adequately capture the decision-making processes for organic food purchasing. We realize that the application of theories that focus on changing behavior (e.g., goal framing theory, impulsive buying theory) in conjunction with theories that emphasize explaining the decision-making process (e.g., TPB, TIB) can improve our understanding of customer behavior. However, we should also remember that while studying a certain behavior through multiple lenses can provide new insights, it may also introduce undesired complexity and make the interpretation of results more challenging. Therefore, a good balance between detail and functionality should be maintained.

From a practical perspective, the classification results suggest that, for the average person, price is still an obstacle to purchasing organic food. The clustering results provide strong evidence of the influence of impulsive, habitual, and normative cues as well as the dual role of emotions in choosing organic products in three distinct consumer segments. In fact, we would have highlighted these two factors (trust and price) as the most important attributes in wine purchasing if we had only used classification algorithms. At the same time, emotions, habits, and impulsive tendencies can prompt unplanned and spontaneous purchasing behavior and can make consumers go against their beliefs. Moreover, the more important price and availability cues are for the consumer (e.g., promotions, shelf accessibility), the more they are prone to spontaneous wine purchasing.

Sales promotions and government subsidies for organic products can support organic purchasing and, at the same time, change consumer consumption habits to help the environment. Retailers can have an organic section in their stores specifically designed to facilitate this behavior. Encouraging a greater sense of joy and happiness in the store, and using social media to advertise a range of organic products, may be other effective mechanisms to change wine purchasing behavior. We might have ignored the influence of affective factors if we had relied only on the results of the classification analysis. Future research would benefit from examining the efficacy of these interventions in shifting behavior towards organic consumption.

ML algorithms can be used to inform the extended supply chain framework (Taghikhah, Voinov & Shukla 2019b) to predict consumer motivation and behavior for green products. The results would also allow us to further calibrate and test the agent-based model, ORVin (Taghikhah, Voinov, et al. 2020b), developed to quantify the cumulative impacts of organic wine preference changes among heterogeneous consumers prone to behavioral biases and social interactions.

5.7. Author contributions

Conceptualization: F.T., A.V., N.S., and T.F.; methodology: F.T., A.V., N.S., and T.F.; software: F.T.; validation: F.T., and N.S.; data collection: F.T.; writing—original draft preparation: F.T.; writing—review and editing: F.T., A.V., N.S., and T.F.; visualization, F.T.; supervision: F.T., A.V., N.S., and T.F.

Appendix 5.A: Questionnaire

Extending supply chain to address sustainability

Dear Respondents,

We are conducting research to understand how people make decisions about the wine they want to drink. The goal of our project is to develop a decision-support tool for transitioning towards more sustainable wine production-consumption. We trust that the choices of customers - as one of the most important stakeholders - are key to such transition.

Your information will enable us to understand the needs of wine consumers and hopefully improve your experience with wine products in the future. The responses to this survey will be anonymous and no identifying information will be linked to your responses after you complete the survey.

Should any questions or concerns arise about the survey or the project in general please send an email to Firouzeh.Taghikhah@uts.edu.au

Q2 Are you...?

- ○ Male (1)
- ○ Female (2)
- ○ Prefer not to say (3)

Q3 Within which age group do you fall?

- ○ 18 to 25 years (1)
- ○ 26 to 35 years (2)
- ○ 36 to 45 years (3)
- ○ 46 to 55 years (4)

- ○ 56 to 65 years (5)
- ○ 66 years or more (6)

Q4 Which of the following best describes your current employment status?

- ○ Unemployed (1)
- ○ Student (2)
- ○ Full-time worker (3)
- ○ Part-time worker (4)
- ○ Retired (5)

Q5 How many people (over 18 years) are continuously living in your household, including yourself?

____

Q6 What is the highest education level in your household?

- ○ Primary (1)
- ○ Secondary (2)
- ○ Graduate (3)
- ○ Post-graduate (4)

Q7 What is the average income of your household?

- ○ Less than $45,000 (1)
- ○ $45,000 to $75,000 (2)
- ○ $75,001 to $150,000 (3)
- ○ $150,001 to $250,000 (4)
- ○ More than $250,000 (5)

Q8 What is your occupation?

- ○ Engineering (1)
- ○ Education (2)
- ○ Sales and service (3)
- ○ Management (4)
- ○ Other (Please specify) (5) ____

Q9 Please indicate in which suburb of the City of Sydney local government area (LGA) you live.

- ○ Alexandria (1)
- ○ Annandale (shared with Inner West Council) (2)
- ○ Barangaroo (3)
- ○ Beaconsfield (4)
- ○ Camperdown (shared with Inner West Council) (5)
- ○ Centennial Park (shared with City of Randwick) (6)
- ○ Chippendale (7)
- ○ Darlinghurst (8)

- Darlington (9)
- Dawes Point (10)
- Elizabeth Bay (11)
- Erskineville (12)
- Eveleigh (13)
- Forest Lodge (14)
- Glebe (15)
- Haymarket (16)
- Millers Point (17)
- Moore Park Newtown (shared with Inner West Council) (18)
- Paddington (shared with Municipality of Woollahra) (19)
- Potts Point (20)
- Pyrmont (21)
- Redfern (22)
- Rosebery (shared with Bayside Council) (23)
- Rushcutters Bay (24)
- St Peters (shared with Inner West Council) (25)
- Surry Hills Sydney CBD (26)
- The Rocks (27)
- Ultimo (28)
- Waterloo (29)
- Woolloomooloo (30)
- Zetland (31)
- Other (Please specify) (32) ____

Q11 Do you like the taste of organic wine?

- Yes (1)
- No (2)
- Neutral (3)

Q12 Do you find a distinction between the taste of organic and conventional wine?

- Yes (1)
- No (2)
- Neutral (3)

Q13 Do you think organic wine is tastier than conventional wine?

- Yes (1)
- No (2)
- Neutral (3)

Q14 How many bottles of wine your household may purchase on average?

- Less than 1 bottle per month (1)

- Less than 5 bottle per month (2)
- Between 5 and 10 bottles per month (3)
- More than 10 bottle per month (4)

Q15 Have you ever purchased organic wine?

- Yes (1)
- No (2)

Q15-1 If "Yes", proportionately, how much of your shopping size is organic wine? (in percent)

- 0% - 25% (1)
- 26% - 50% (2)
- 51% - 75% (3)
- 76% - 100% (4)

Q16 Do you buy organic wine for special occasions?

- Yes (1)
- No (2)

Q17 How often do you drink wine?

- Every day (1)
- 4-5 times a week (2)
- 2-3 times a week (3)
- Once per week (4)
- Few times a month (5)
- Once per month (6)
- Few times in a year (7)

Q18 How frequent do you purchase wine?

- Every day (1)
- 4-5 times a week (2)
- 2-3 times a week (3)
- Once per week (4)
- Few times a month (5)
- Once per month (6)
- Few times in a year (7)

Q19 How much time do you usually spend in a wine shop?

- Less than 15 mins (1)
- Between 15-30 mins (2)
- More than 30 mins (3)

Q20 Do you buy wine of a particular brand every time?

- Always (5)

- Sometimes (4)
- Maybe (3)
- Seldom (2)
- Never (1)

Q21 Please rate the following statement when thinking of purchasing wine.
Purchasing a certain type/brand of wine (either conventional or organic) is something that...

	Strongly agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly disagree (1)
I do frequently (1)	o	o	o	o	o
I do automatically (2)	o	o	o	o	o
I do without thinking (3)	o	o	o	o	o
belongs to my (daily, weekly, monthly) routine (4)	o	o	o	o	o
I start doing before I realize I'm doing it (5)	o	o	o	o	o
I would find hard not to do (6)	o	o	o	o	o
I have been doing for a long time (7)	o	o	o	o	o

Q22 Please respond to these statements by indicating true or false and if not sure, indicate so.

	Strongly agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly disagree (1)
Chemicals used for wine production have an effect on the environment (1)	o	o	o	o	o
Wine produced from grapes grown with no chemical application is higher in antioxidants (2)	o	o	o	o	o
The antioxidant in wine helps to	o	o	o	o	o

reduce cholesterol in the blood (3)					
Consumption of naturally produced products reduces diseases risk (4)	o	o	o	o	o
Organic wine has specific health benefits that reduce the risk of developing diseases (5)	o	o	o	o	o
Added chemicals in wine have long term effects on consumer health (6)	o	o	o	o	o

Q23 *Please state your level of agreement with each of these statements:*

	Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly disagree (1)
I believe that climate change is real and I am very concerned (1)	o	o	o	o	o
If we continue on our present course, we will soon experience a major ecological catastrophe (2)	o	o	o	o	o
I think that humans are responsible for climate change issues (3)	o	o	o	o	o
I think organic vs conventional farming increases species richness and benefits biodiversity (4)	o	o	o	o	o
I would be willing to change my behaviour to address	o	o	o	o	o

environmental concerns (5)					
By changing my shopping habits, I can affect other people's habits (6)	o	o	o	o	o
I do not purchase products that damage the environment (7)	o	o	o	o	o
I feel that by purchasing organic (bio) food products, I can protect the environment (8)	o	o	o	o	o
I would like to have more information about organic products (9)	o	o	o	o	o
I am willing to spend more money on organic products (10)	o	o	o	o	o
I prefer organic wine to non-organic wine since it is healthier (11)	o	o	o	o	o
I look for sustainability labels when I go shopping (E.g. NASAA, ACO, OGA organic, Principles/Practices, DEMETER Biodynamic) (12)	o	o	o	o	o

Q24 Please indicate your level of support for these statements.

	Strongly agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly disagree (1)
I trust in the health and environmental benefits of organic wine (1)	o	o	o	o	o
I trust in the originality of organically	o	o	o	o	o

labelled/claimed wine (2)					
I trust that my purchase of organic wine helps to promote sustainable lifestyle (3)	o	o	o	o	o
I trust Australian institutions that certify organic foods (4)	o	o	o	o	o

Q25 Please consider the hypothetical situation of choosing a bottle of wine for family consumption from the supermarket shelf:

Please rank the following decision factors based on their importance to you. (1= least important, 5=most important)
______ Price of wine (1)
______ Health benefit of wine (2)
______ Environmental benefit of wine (3)
______ Convenience (4)
______ Advice of others (5)

Q26 How much do you pay on average for a bottle of wine?
o Less than 15 (1)
o 15-30 (2)
o 31-50 (3)
o 51-70 (4)
o 71-100 (5)
o More than 100 (6)

Q27 What is the maximum amount you would pay for a bottle of wine?
____

Q28 Are you willing to pay more for organic wine compared to a conventional wine with similar characteristics?
o Yes (1)
o No (2)

Q29 How much more are you prepared to pay for an organic-labelled certified wine bottle over the "everyday price" (Assume that everyday price is 10$ per bottle)?
o Not willing to pay more (1)
o Willing to pay less than 10% more (2)
o Willing to pay less than 20% more (3)
o Willing to pay less than 30% more (4)
o Willing to pay less than 40% more (5)
o Willing to pay over 50% more (6)

Q30 How often do you compare prices of different wines?
o Every time you purchase wine (1)

o Every other shopping (2)
o Quite often (3)
o Rarely (4)
o Seldom (5)
o Never (6)

Q31 What will you do if the price of your favorite wine increases by 20%-30%?
o Check the price of other wines and buy a cheaper wine (1)
o Will not buy wine and wait until its price decreases (2)
o Will buy my favorite wine at the new price (3)

Q32 What will you do if your favorite wine is not available at the store?
o Will not buy wine and will wait until my next shopping for wine (1)
o Check stores of other Sydney areas to get my favorite wine (2)
o Buy other available wines if it costs less (3)
o Buy other available wines if it has the same price (4)
o Buy other available wines even at higher prices (5)
o Do not know (6)

Q33 Please rate to what extent does the choices (or advice) of these people influence your wine preferences:

	Strongly agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly disagree (1)
Family (1)	o	o	o	o	o
Friends (2)	o	o	o	o	o
Other shoppers at store (3)	o	o	o	o	o
Shop staff (4)	o	o	o	o	o
Social/mass media, commercials (5)	o	o	o	o	o
(6)	o	o	o	o	o

Q34 How often do you talk with family, friends and neighbours about your drink choice?
o Every day (1)
o Every week (2)
o Every month (3)
o Every couple of months (4)
o Every year (5)

Q35 Please indicate your level of support for these statements.

	Strongly agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly disagree (1)
Shopping is one of my favorite activities. (42)	o	o	o	o	o

I felt excited on this shopping trip (43)	o	o	o	o	o
I felt happy during the shopping trip (44)	o	o	o	o	o
I experienced a number of sudden urges to buy things I had not planned to purchase on this shopping trip (45)	o	o	o	o	o
When I go shopping, I buy things that I had not intended to buy (46)	o	o	o	o	o
It is fun to buy spontaneously (47)	o	o	o	o	o

5.A2. Classification algorithms

In conducting classification, both parametric (e.g., Logit Regression) and non-parametric (e.g., Support Vector Machine, Decision Tree, and Random Forest) classification algorithms have been used. We compare the advantages and disadvantages of non-parametric algorithms and then describe the corresponding mathematical formulation in Table 5.A1.

Table 5.A1. Technical information for non-parametric classification algorithms.

Supervised learning	Advantage	Disadvantage	Mathematical formulation	Reference
Support Vector Machine	-Suitable for highly dimensional databases, especially if the number of records is slightly lower than the number of features. -High memory-performance efficiency because only a subset of training data is used in the decision function.	-The issue of over-fitting is likely to occur if the number of records is significantly lower than the number of features. -Rather than estimating probabilities directly, an expensive five-fold cross-validation provides the estimations.	Assume training vectors $x_i \in \mathbb{R}^p$, i=1,…, n, and $y \in \{1,-1\}^n$, the objective function can be defined as: $\min_{w,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \zeta_i$ subject to $y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i$ $\zeta_i \geq 0, i = 1, \ldots, n$ So the dual is $\min_{\alpha} \frac{1}{2} \alpha^T Q \alpha - e^T \alpha$ subject to $y^T \alpha = 0$ $0 \leq \alpha_i \leq C, i = 1, \ldots, n$ where C>0 is the upper bound, Q is an n by n positive semidefinite matrix, $Q_{ij} \equiv y_i y_j K(x_i, x_j)$, and $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ is the kernel. The decision function is: $\operatorname{sgn}(\sum_{i=1}^{n} y_i \alpha_i K(x_i, x) + \rho)$	https://scikit-learn.org/stable/modules/svm.html#classification
Decision Tree	-Visualizing tree facilitates the understanding and interpretations of results. -The need for data preparation, such as handling dummy variables, normalization, etc. is significantly lower compared to other algorithms. -Efficiency in dealing with both numerical and categorical data as well as multi-output problems.	-The issue of over-fitting is likely to occur if parameters such as the minimum sample size required at a leaf node, the pruning method, or the tree depth are not set correctly. -Highly sensitive to the variations in the data, which can lead to the issue of instability. This may limit the generalizability and robustness of the results. -If the dataset is unbalanced (one class dominate or underrepresented), the generated tree may be biased.	Assume training vectors $x_i \in R^n$, i=1,…, l and a label vector $y \in R^l$, space is partitioned by a decision tree in a way that it can group the same labeled samples. If the data at node m is presented by Q, each candidate split $\theta = (j, t_m)$, j refers to feature and t_m refers to the threshold. Data is portioned into below subsets: $Q_{left}(\theta) = (x, y) \| x_j <= t_m$ $Q_{right}(\theta) = Q \setminus Q_{left}(\theta)$ Then, impurity function H() calculates the impurity of subsets as: $G(Q, \theta) = \frac{n_{left}}{N_m} H(Q_{left}(\theta)) + \frac{n_{right}}{N_m} H(Q_{right}(\theta))$ And minimizes the impurity by selecting θ as: $\theta^* = \operatorname{argmin}_\theta G(Q, \theta)$	https://scikit-learn.org/stable/modules/tree.html#classification
Random Forest	-Addressing concerns with generalizability and robustness over a single tree by combining the predictions of several trees.	-Providing a black-box model, where the results cannot be easily explained and interpreted.	NA	https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.Random

	-Avoiding the problem of trapping in local optimal because multiple trees are trained in an ensemble learner so that the global optimal can be detected.			ForestClassifier.html#sklearn.ensemble.RandomForestClassifier

5.A3. Clustering algorithms

In contrast to the convex-shaped clusters in K-means, the clusters in DBSCAN algorithm can be of any shape. Figure 5.A1 demonstrates the differences between various clustering algorithms. This algorithm separates the high-density areas, called core samples, from each other by the low-density areas. In fact, a cluster is composed of a set of core samples that are near to each other (through detecting all of its neighboring core samples and then neighbors of neighbors). By determining two parameters, min_samples and eps, we can define the desired density for forming a cluster. min_samples determines the tolerance of the algorithm towards noise, while eps is to control the local neighborhood of the points. For example, lower min_samples and higher eps indicate we aim to find lower density clusters. Outliers or noises are the non-core samples that are at least eps and far from all the core samples. If the database is noisy and large, it may be desirable to choose eps large enough; otherwise, the algorithm would label most data as noise. Having said that a very large eps might merge the close clusters into one. Hierarchical Density-Based Spatial Clustering (HDBSCAN) is an extension of DBSCAN, which has higher performance and more robust results as it can detect clusters of variable densities. For finding more information about this algorithm, please read the study of McInnes & Healy (2017) and Campello, Moulavi & Sander (2013), while for its implementation, please refer to https://hdbscan.readthedocs.io/en/latest/.

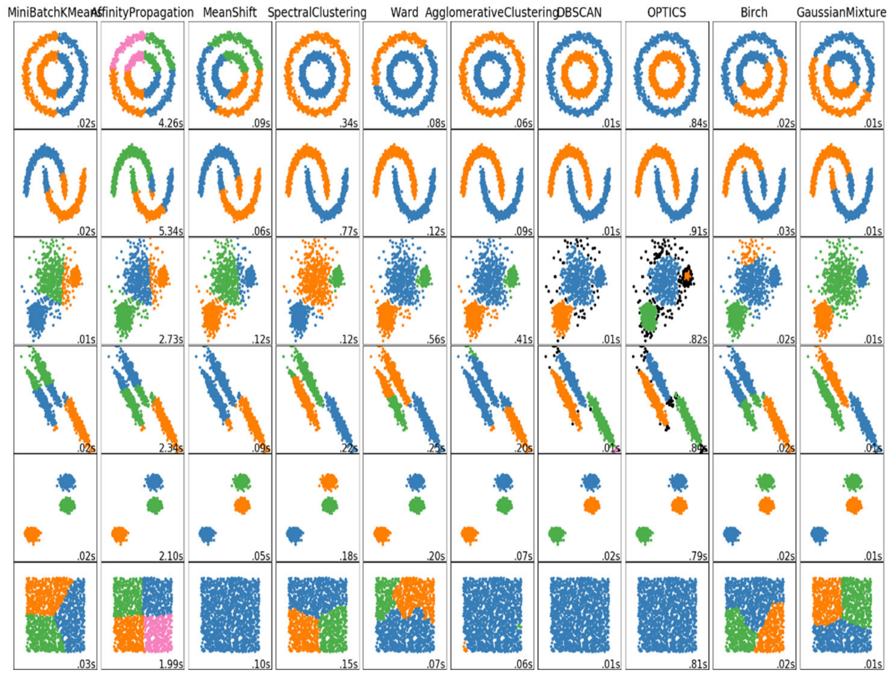


Figure 5.A1. A comparison between clustering algorithms (reference: scikit-learn https://scikit-learn.org/stable/modules/clustering.html#overview-of-clustering-methods)

We use Rahmah & Sitanggang (2016) method for automatically determining optimal epsilon value (which defines the maximum distance between two points). This method calculates the distance between a point and its closest neighboring points, sorts, and plots them. Optimal epsilon is where the slope of plot significantly changes. In Figure 5.A2, this value is found to be at the point of maximum curvature, which is 0.64. This point indicates the area which has the highest density of hotspots. However, the minimum sample size, which is another hyper-parameter of HDBSCAN, is determined experimentally. According to Siddiqui (2013), there is no best practice for obtaining minimum sample. We repeat the analysis multiple times, tuning the algorithm with a fixed epsilon value and different sample sizes, and find the clusters with the highest density and lowest noise at size 4.

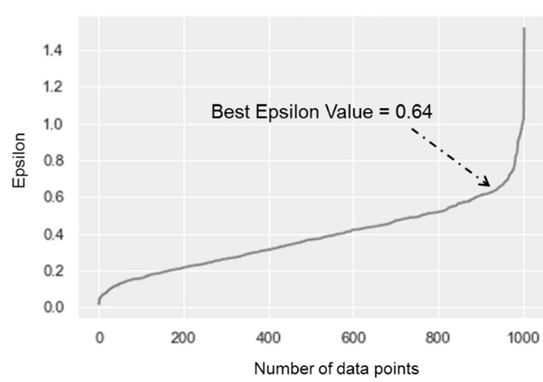


Figure 5.A2. The optimal value for epsilon.

Appendix 5.B: Correlation analysis

Figure 5.B1 presents the heat map of correlations among all the variables.

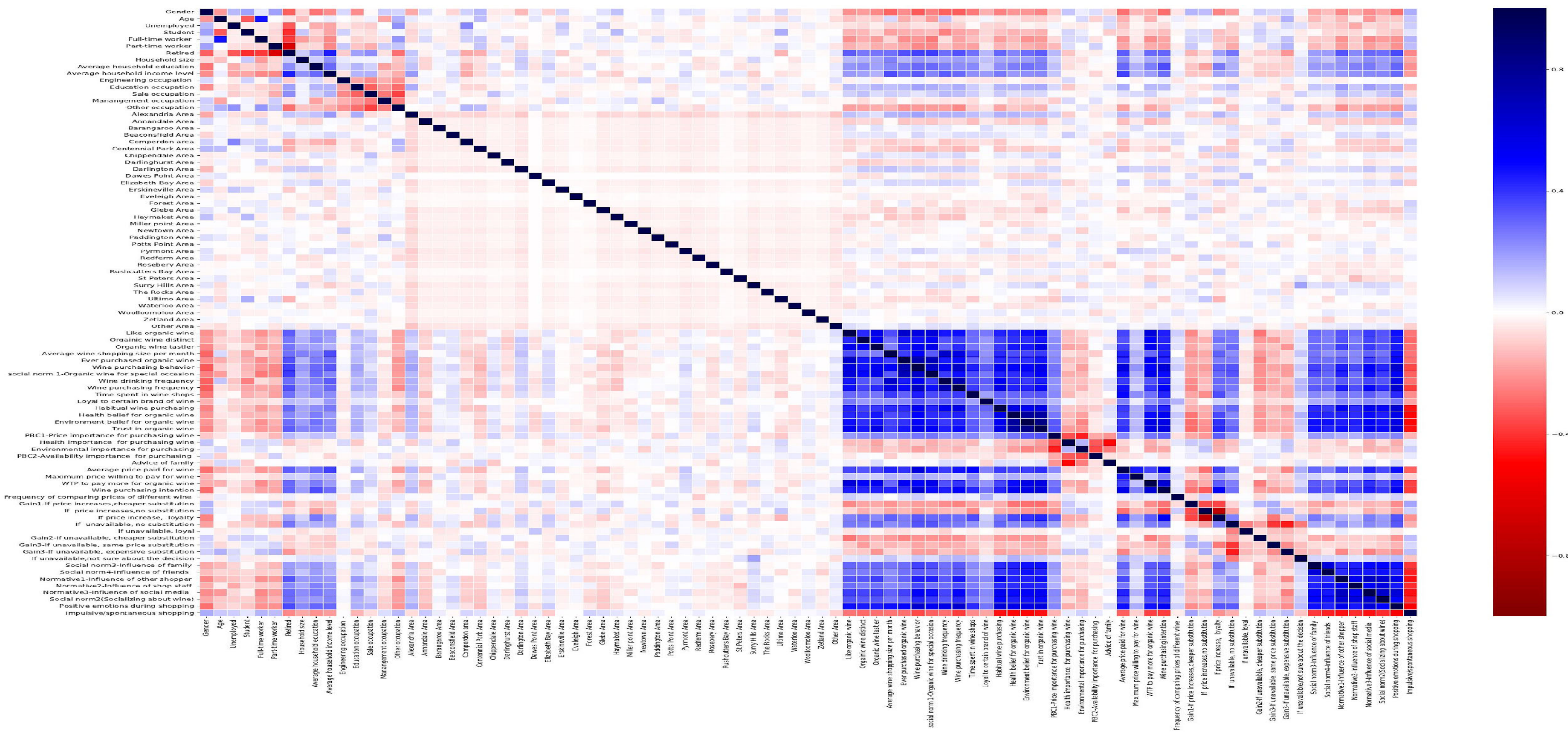


Figure 5.B1. Heat map of correlations among all the variables.

Appendix 5.C: Classification details

5.C1. Intention prediction

We assess the accuracy of predictive models provided by different algorithms for estimating the probability of organic purchasing intention. The dependent variable, willingness to pay a premium for organic wine, consists of 6 ordered-response, known as classes. It is to be noted that we exclude two variables related to behavior: “WTP more for organic wine” (to predict behavior without intention) and “ever purchased organic wine” (to avoid bias), from the list of predictive features. Both these variables had a high correlation with the probability of purchasing organic wine. As shown in Figure 5.C1, after training algorithms, the accuracy of the testing dataset does not exceed 50%. All the obtained models produce consistent errors in misclassifying class (2) and (3). The misclassification indicates homogeneity between the consumers who are likely to pay 10% and 20% more for organic wine. Thus, we combine these two classes into one in an attempt to boost the performance of algorithms. The accuracy of the 5-class model ranges from a minimum of 43% in LR to a maximum of 63% in RF, a growth of 26% compared to the 6-class model. As measured by the error rate in the confusion matrix, the algorithms fail to correctly classify classes (4) and (5), highlighting a high similarity between consumers who are willing to pay up to 30% and up to 40% more for organic wine. After combining these two classes, the 4-class RF model achieves the highest accuracy of 75% (refer to Figure 5.C3), 20% higher than the 5-class model.

On the basis on ML results, we conclude that predictive models can best calculate the likelihood that a consumer is “not willing to pay” (a premium), “willing to pay 10% and 20% more”, “willing to pay 30% and 40% more”, and “willing to pay 50% and higher more.” Moreover, in all the presented experiments, the RF outperforms all the other algorithms (DT, SVM, and LR), while LR has the lowest accuracy. Apparently, the non-parametric algorithms can better handle homogeneity amongst classes that resulted in higher accuracy and demonstrate higher efficiency in processing complex and highly dimensional datasets.

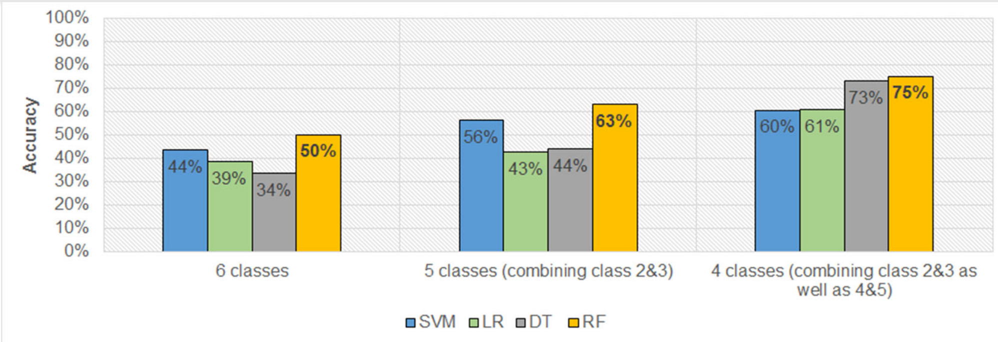


Figure 5.C1. Comparing the performance of algorithms in predicting consumers' intention across three models.

Apart from delivering predictive models, RF provides a deeper understanding and useful information about the relative importance of different variables affecting overall accuracy. We use the Gini importance method to quantify the influence of each predictor (variable) in explaining the intention of consumers for organic wine. This method calculates the reduction in a node impurity (i.e., number of samples that reach the node/ total number of samples) weighted by the probability of reaching that node. A higher value for a variable indicates its higher importance in the prediction. The variables with importance values lower than 0.02 have a negligible impact on the accuracy and are removed from the model. Decision tree model for 4 class intention is presented in Figure 5.C2.

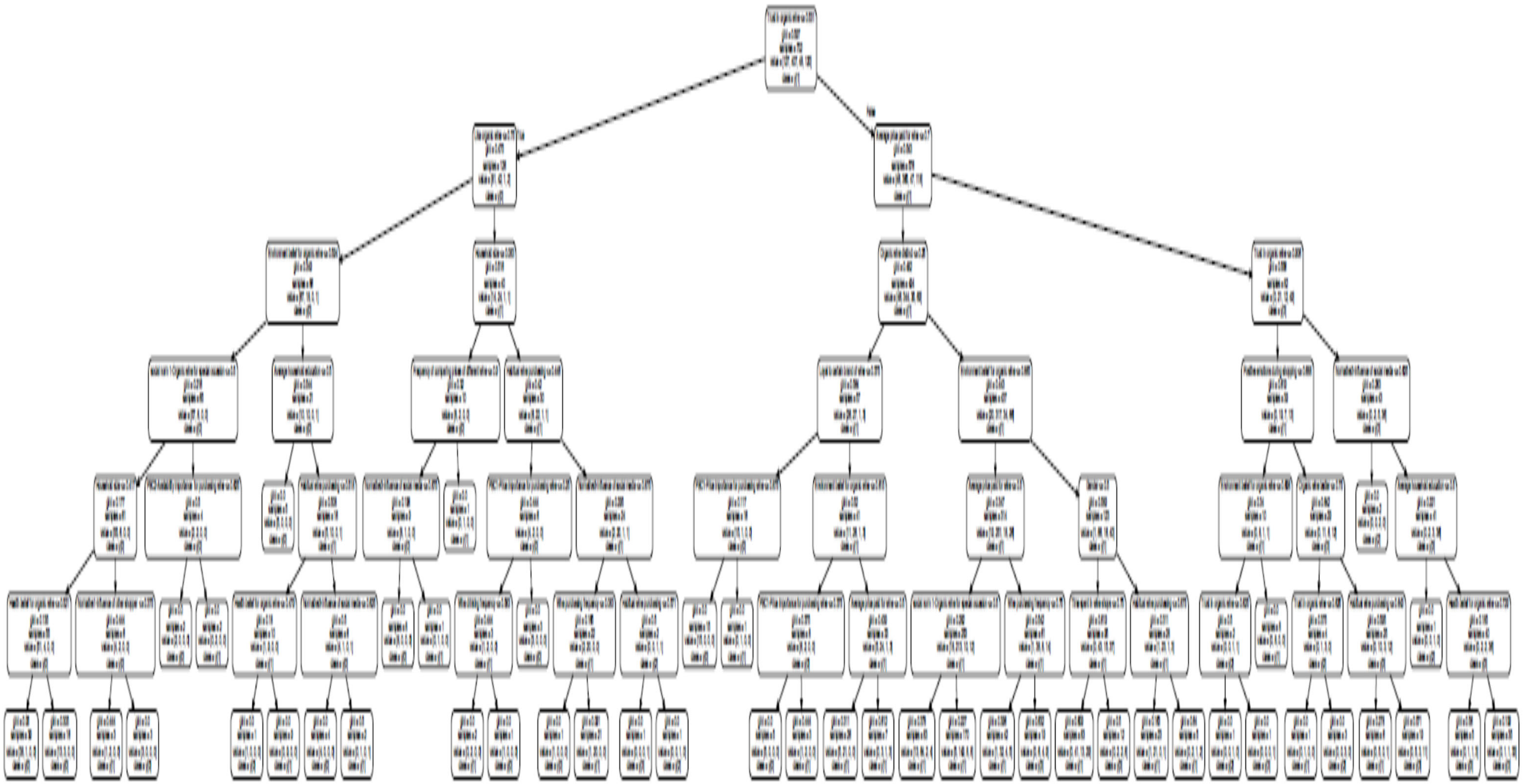


Figure 5.C2. The decision tree for 4 predictive class model of intention for organic wine.

```
[[ 34  20   0   0]
 [  2 160   6   5]
 [  0  14   3   3]
 [  0  21   4  29]]
              precision    recall  f1-score   support

         0.0       0.94      0.63      0.76        54
        0.33       0.74      0.92      0.82       173
        0.66       0.23      0.15      0.18        20
         1.0       0.78      0.54      0.64        54

    accuracy                           0.75       301
   macro avg       0.68      0.56      0.60       301
weighted avg       0.75      0.75      0.74       301

0.7508305647840532
```

Figure 5.C3. Confusion matrix for 4-class intention.

5.C2. Behavior prediction

We assess the accuracy of predictive models provided by different algorithms for estimating the probability of purchasing organic wine. It is to be noted that we exclude two variables related to the behavior (i.e., "WTP more for organic wine" as well as "ever purchased organic wine") from the list of predictive features to avoid bias. As shown in Figure 5.C4, the accuracy of the testing dataset ranged from 30% in SVM to 63% in RF. The algorithms misclassified class (2) and (3), (4) indicating homogeneity between the consumers with a proportion of 25%, 50%, 75% organic wine in their wine shopping baskets. The improvements from combining class (2) and (3) are presented in the 4-class model with the highest accuracy of 74% in RF. We continue boosting the accuracy by integrating class (4) into already combined class (2) and (3) and reach a maximum accuracy of 89% (refer to Figure C6). Similar to intention prediction, for predicting behavior, RF outperforms the other algorithms, but SVM has the worst performance. Moreover, DT and LR demonstrate comparable performance except in predicting 3 classes where DT outperforms.

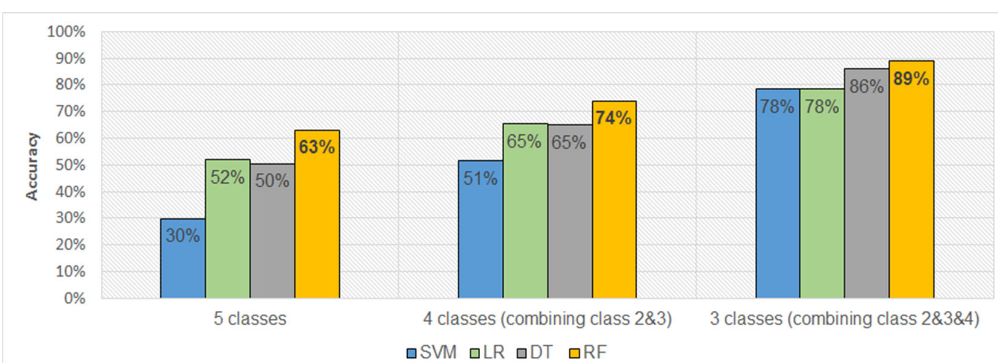


Figure 5.C4. Comparing the performance of different algorithms in predicting wine purchasing behavior.

We then measure the Gini importance for all predictor variables and keep the significant ones in the model. However, we find that there is no full agreement among models about the importance of factors. For example, the 5-class model reports that positive emotions and the average price paid for wine have the strongest influence, while the 4-class model highlights special occasions as the most important factor. Thus, we test the performance of models when the intention variable is included in our analysis as another predictive factor. Decision tree model for 3 class behavior is presented in Figure 5.C5.

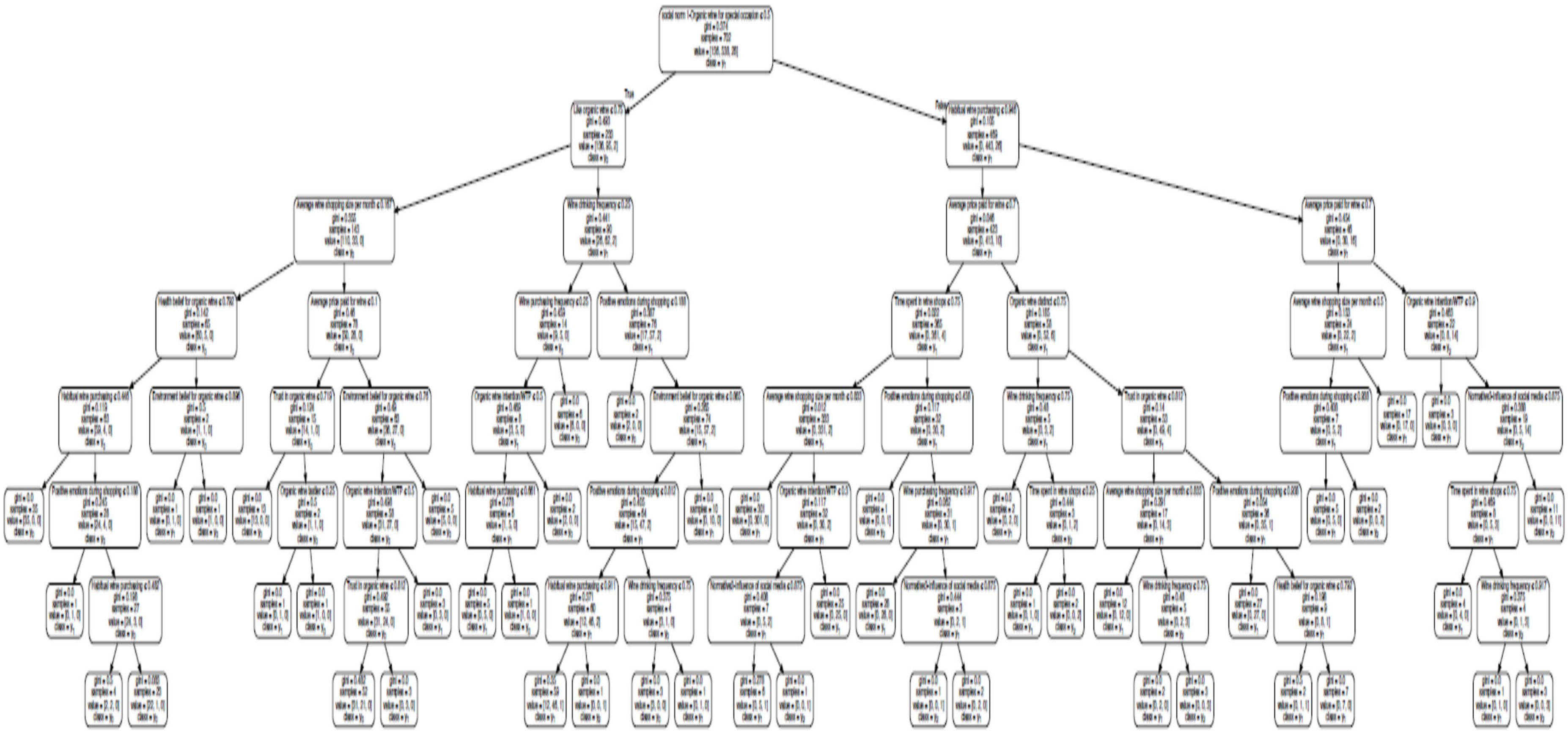


Figure 5.C5. The decision tree for 3 class predictive model of behavior for organic wine.

```
[[ 50  12   0]
 [  7 211   0]
 [  0  14   7]]
              precision    recall  f1-score   support

         0.0       0.88      0.81      0.84        62
         0.5       0.89      0.97      0.93       218
         1.0       1.00      0.33      0.50        21

    accuracy                           0.89       301
   macro avg       0.92      0.70      0.76       301
weighted avg       0.90      0.89      0.88       301

0.8903654485049833
```

Figure 5.C6. Confusion matrix for 3-class behavior.

5.C3. Random forest factor importance for behavior (excluding intention)

Table 5.C1 presents the importance of factors in RF algorithm for purchasing organic wine behavior when the intention factors are excluded from prediction.

Table 5.C1. The importance of factors in RF algorithm for purchasing organic wine behavior when the intention factors are excluded from prediction.

Factors	Variables used in RF model	Importance in 5 class model	Importance in 4 class model	Importance in 3 class model
Behavioral factors	*Positive **emotions****	0.06	0.04	0.07
	*Organic wine for **special occasion****	0.05	0.07	0.11
	Talking about wine when **socializing**	-	0.02	-
	***Trust** organic wine**	0.03	0.03	0.02
	Health belief about organic wine	0.03	0.03	-
	Environmental belief about organic wine	0.03	-	-
	Wine **availability** importance	0.02	0.02	-
	***Like** organic wine**	0.05	0.07	0.10
	***Distinction** between organic and conventional wine**	0.03	0.04	0.05
	Perceive organic wine **tastier**	-	0.02	0.02
	Habitual wine purchasing	0.03	0.04	-
	***Impulsive** shopping tendencies*	0.02	-	-
Drinking style factors	***Average price** paid for wine**	0.06	0.06	0.08
	*Wine **purchasing frequency****	0.05	0.07	0.05
	***Time spent** in wine shop**	0.04	0.04	0.05
	*Wine **drinking frequency****	0.03	0.04	0.05
	*Average wine **purchasing size****	0.03	0.05	0.04
Socio-demographics factors	**Age**	0.02	0.03	-
	Household size	0.02	-	-

Chapter 6:

Conclusions and future work

This aim of this Ph.D. research is to assess the contribution of consumer behavior changes in improving the socio-environmental impacts of SCs. We seek to achieve this aim by: (a) proposing a conceptual framework, ESSC, to better address sustainability issues in SCs (Chapter 2); (b) developing a simulation model to understand consumer behavior and evaluate the effectiveness of different interventions on changing consumer preference s into organic food (Chapter 3); (c) designing a simulation model to quantitatively assess the impacts of changing consumer choices on the performance of ESSC (Chapter 4); and (d) conducting an empirical study to examine the gap between consumer purchasing intention and actual behavior (Chapter 5). We provide an overview of this thesis findings for each chapter, its implications and recommendations for research, practice and policy, and future research directions as below.

6.1. Overview of findings

1. *<u>Extending the supply chain to address sustainability:</u>*

In Chapter 2, we suggest that an extension of the supply chain concept is needed if we want to analyze their sustainability. First, we present an overview of the evolution of the SC concept with respect to sustainability goals. To this end, we select some of the most relevant papers and critically compare and contrast them. Summarizing literature on sustainable supply chains, circular supply chains and sustainable circular supply chains, we show why they were not quite adequate to address the holistic and system wide sustainability issues. We discuss the sustainable forward logistics issues in SSC and the integration of circular economy concepts with the supply chain organization. The relationship between LCA methodologies and CSC is examined in the context of sustainable CSC. This review clearly demonstrates how the SC concept has been evolving to include additional processes and actors, to consider the requirements of sustainable development.

Next, we show how financial performance of supply chains may be influenced as a result of implementing green practices such as green technology, green product design, and end of life treatment. Most supply chain managers conclude that their competitiveness is eroded with increases in the cost of green products. Furthermore, we explain consumer choice behavior in purchasing green products and strategies to motivate pro-environmental behavior. By doing so, we set the foundation to consider the role of green product consumers in SSC.

To address sustainability in future research on SC we propose a conceptual framework which links three very different areas

- Supply chain design and engineering,
- Financial performance, accounting and economic optimization and,
- Consumer behavior and environmental psychology.

Our findings demonstrate how financial performance of SSC can be improved by bringing the consumer into the picture and exploring how their willingness to pay and sustainability concerns can be influenced and modified. Although it is important for the focal firms to identify possible strategies for motivating pro-environmental behavior of stakeholders, particularly consumers, SSC studies are still far from providing comprehensive analytical studies. Disregarding the relations between SSC and consumer behavior leads to a blurred notion of sustainability in supply chain research. We argue that for transition towards sustainability, it is crucial to take the extended supply chain view, in which the boundaries are expanded towards the involvement of consumers and their behavior.

2. *Exploring consumer behavior and policy options in organic food adoption: Insights from the Australian wine sector:*

Following the idea of ESSC, we narrow down the scope of the thesis into agro-food SC to explore the key stimuli that lead people to make choices between organic and non-organic food in the complex shopping environment. Chapter 3 focuses on the demand side of organic food market and quantifies the cumulative impacts of behavioral changes among heterogeneous consumers, prone to behavioral biases and social interactions. We take organic wines as an example, but the approach is transferable to analyze other food markets where consumers choose between conventional and organic products. We develop a spatial ABM, ORVin, grounded in theory and data to understand wine purchasing behavior. The model could be a part of the extended supply chain framework (Taghikhah et al., 2019), that highlights the significance of raising consumer awareness and motivating behavioral shifts for reducing the environmental impacts of food production. We believe that the role of consumers and their preferences is an important factor in shaping the transition to a sustainable food supply chain.

We then explore the role of different policy interventions such as taxation and public awareness campaigns in promoting the demand for organic wine. A combined market and information-based policy is more effective in promoting organic wine preference than applying these policies separately. This non-additive effect of policies is an emergent property in this system and is explained as following.

- Behavioral shifts occur when the social pressure for purchasing conventional wine reduces. Jager and Ernst (2017) suggest this phenomenon is caused by co-dependent behaviors, where individual behavior is amplified by its social environment. They state that "the coupling results in social processes that may become self-amplifying: the more people change, the stronger the social pressure on other people to change as well."
- A cascade of behavior changes for purchasing organic wine is triggered by getting over the 35% tipping point, which can be achieved only by combining two strategies. This radical change does not occur even if more than a third of the population adopt organic wine in response to separate interventions.
- Conformity rather than social learning plays the dominant role in purchasing contagious products, including wine. As organic wine purchasing behavior gains more visibility, it is more likely to gain social approval. The norm for conventional wine purchasing in a vicious cycle can shift to organic wine purchasing in a virtuous cycle and get reinforced.

This finding is important for increasing the adoption of organic vice products where the willingness to pay is profoundly lower than for virtue products, even with the same price premiums. Organic vice products suffer from negative quality inferences, which can be reduced in social consumption situations/environments (Mollen et al., 2013). Therefore, if the concerns for public self-image and norm conformance representing undercover altruism are alleviated, the number of organic vice consumers is expected to surge.

3. *<u>Integrated modeling of extended agro-food supply chains: A systems thinking approach:</u>*

Following the development of ORVin, we demonstrate an approach for modelling the ESSC framework and its operationalization. Chapter 4 focuses on a multi-echelon supply chain network in the context of the agro-food industry to investigate the impact of shifts from conventional to organic food consumption on the underlying SC activities and behaviors. It comprises a set of farmers, processors, distributors, retailers, and customers; producing and consuming both organic and conventional food. In doing so, an integrated modelling approach combining ABM, DE, and SD help us to simulate the operations and decisions of each actor autonomously. We assess the performance of the proposed model in terms of economic, environmental, and social metrics.

ESSC suggests further integration of consumer behavior models as sub-models into traditional SSC models. This integration not only reveals the unobserved preference heterogeneity in consumers, but also discloses a two-way influence between consumption patterns and production-distribution decisions. Findings from these production-consumption interaction include:

- The negative impact of uncertain prices on farmers' expectations of organic adoption: The unpredictable and erratic organic prices causes an uncertainty in farmers' expectations about its future returns. As it is unclear when organic wine prices would recover or stabilize, farmers started to perceive conventional markets more. They perceive entering organic markets as a promising strategy if the price for organic wine rises or remains relatively stable following the conversion from conventional farming. Thus, in the volatility of conventional wine price but stability of organic price, farmers tend to perceive the value of waiting to convert higher and risks in the future of organic farming lower.

- Slow propagation of consumers' organic preferences through agro-food SC: The adaptation of SC operations to the dynamic market trends take a considerable amount of time. As there are two echelons between the consumers and farmers, transmitting the feedback/ market signals from the preferences of consumers to the land management decisions of farmers. Taylor (2006) and Naik and Suresh (2018) emphasize that the operational and structural factors such as long lead times, absence of long-term demand forecasts and etc. account for this gap between agricultural production and consumer demand.

- Social norms can powerfully change consumers' wine preferences: It is interesting to observe that minor changes in the consumption side can help to improve the socio-environmental performance of agro-food SC. The social norms manipulation (reducing neighborhood effect) promotes ecological behavior more significantly than economic factors (consumer income growth). It is quite challenging to motivate consumers to spend more on organic products in the absence of supportive norms, even if their income level is higher. As social norms exert a strong effect on food consumption and production behavior, considering them in the management of SSC can provide new insights.

4. <u>The interplay of cognitive and affective factors in purchasing behavior: Insights from machine learning for an organic wine case study:</u>

Chapter 5 shows an approach for collecting observational data to parameterize the ESSC and providing empirical evidence to examine the model assumptions. It underscores the importance of considering impulsive and unplanned as well as planned decisions in understanding food purchasing behavior. An integrative theoretical framework theoretically explains consumers' purchasing behavior considering both cognitive (attitudes, subjective norm, PBC, and habits) and affective factors (emotions, impulse tendencies, and personal goals). We quantitatively assess the relevance of behavioral factors in an organic wine case study. Following, the wine preferences of 1003 Australians are collected through a survey. The descriptive analysis highlights a gap between intention and behavior, where 80% state to have a willingness to pay more for organic wine, only 20% buy organic wine almost exclusively. Correlation analysis reveals emotions positively, while impulse tendencies negatively correlate to cognitive factors. Thus, the likelihood of spontaneous purchasing is higher when the consumer is experiencing negative emotions. Regarding personal goals, normative and hedonic goals are positively related to the cognitive and affective factors except impulse tendencies. Gain goals, however, are contrary to all the other factors (excluding impulse tendencies), where they can weaken the influence of attitude, emotion and hedonic goals. This implies the more importance consumers give to the price and availability cues (e.g., promotions, shelf accessibility), the more they are prone to unplanned purchasing. These findings also confirm the differences between the causal mechanism of unplanned and impulsive behaviors.

Using both supervised and unsupervised machine learning methods, we provide models to predict the likelihood of purchasing organic wine and segregate consumers based on their similarity. We use socioeconomic characteristics, shopping-drinking style, and behavioral factors to train four different classification algorithms; support vector machine, logistic regression, decision tree, and random forest. Concerning the prediction accuracy, RF outperforms all the other algorithms. It recognizes trust and the average price paid for wine as the most important predictive factors and marks them as the sources of heterogeneity in consumers' intention and behavior for organic wine, respectively. RF intention prediction models rely on attitudes, emotions, hedonic goals, habitual purchasing, and the frequency of wine drinking and purchasing. RF behavior prediction models add normative support provided by social media and purchasing occasions to the list of influential factors.

DBSCAN, a density-based clustering method, helps in deriving six clusters of consumers with planned, unplanned and impulsive behaviors. This method reveals that high impulsive tendencies can lead to the spontaneous purchasing of organic and conventional wine depending on emotional direction. In the presence of extreme positive emotions, consumers' willingness to pay more for organic wine and the average price paid for wine will increase, whereas negative feelings prompt intention and behavior for conventional wine purchasing.

6.2. Implications and recommendations

Recommendation 1:

We invite sustainable supply chain analyses to go beyond their traditional scope of operations, and bring consumer behavior dynamics into consideration. It is important to identify the factors influencing consumer choice behavior regarding sustainable products and apply appropriate interventions to change unsustainable consumer behavior. The growing field of behavioral and empirical economics and the proliferation of agent-based modelling methods, can now look at heterogeneous human behavior under various conditions, and can help understand and quantify some of the cultural and social drivers that affect SC (Filatova et al., 2013; Anufriev et al., 2018). These models can be well integrated with SSC models to include the social dynamics in SC design and management (Taghikhah et al., 2018). They can be used to improve SCM and offer additional control parameters for optimization of SC performance. The ESSC framework assumes that other managerial techniques should also be employed, with a focus on the social dimension, on education, motivation, nudging and persuasion as part of development towards sustainability.

We hope that the ESSC framework can help supply chains to become green and to gain competitive advantage and improve visibility of sustainable practices in the evolving marketplace. A future extension of this research will consist of developing analytical studies to compare the performance of extended sustainable supply chain with conventional frameworks. Another extension can be to empirically analyze the impact of adopting behavioral change strategies for green demand and green supply. Future studies can develop tools and models to deal with the difficulty of prediction and high uncertainties involved in behavioral aspects of green consumption.

Recommendation 2:

Although the examined strategies are hypothetical, they have real-world policy implications for the food and wine sectors. From a food marketing perspective, while big supermarkets and food companies push for launching alternative organic food products, the small market size, and low willingness to pay for them hamper their prosperity. To successfully promote organic vice product lines, a combination of price promotion and normative cues can create major change. Price promotions are effective in attracting new consumers. Cues promoting organic purchasing as a common norm manipulate people's anticipation about possible reactions of others (conventional consumers) and allow them to make a moral choice.

From an agricultural perspective, the Australian Grape and Wine Authority is actively looking for new methods and technologies to enhance the sustainability of wine industry and improve resource management (Australia, 2019). They emphasize that organic is most likely to become a major competitive advantage in the international market. ORVin contributes to this debate, adding insights about how Australian consumers' interests in eco-friendly wines can help to expand the organic trend domestically. It also tells policymakers how to provide additional support for organic farmers by changing consumers' expectations about the wine choice of others. From the health perspective, ORVin can help designing programs for encouraging healthier lifestyles and reducing the health-environmental risks of wine drinking.

Recommendation 3:

The comparison between the results of ESSC and SSC indicates that the assumptions of homogeneity in consumer preferences may predispose the estimation of traditional SSC models to skepticism and bias. The homogeneous demand assumption has the highest impact on estimation of behavioral and environmental performance. Our modeling experiment demonstrates the adaptiveness of ESSC model to the market dynamics. The findings with respect to the changes in the financial and behavioral status of consumers, highlight the highest impact of changing social norms on improving the sustainability of the SC. As there are multiple actors between the consumers and suppliers, farmers' perception and expectations towards the value of organic based agriculture may deviate notably from the reality. Moreover, the adaptation of producers to the market trends takes a considerable amount of time due to the delays in supply. The analysis considering the optimal scenarios shows solutions that can simultaneously improve the economic, social, and environmental performance but not the behavioral performance. This means that by the expansion of organic farming in response to the growing demands of organic consumers, a significant reduction in the organic wine prices will eventually occur that is not favorable to the farmers.

Accounting for demand side heterogeneity provides new insight into addressing sustainability issues in SCs. The results imply that the design of organic food policies aiming at behavioral changes should not be limited to financial incentives. In designing politically feasible policy options, paying attention to the social environment, public awareness, norm support cues, and cultural codes can reinforce the transition into organic food consumption. Accompanying information and value based policy instruments may lead to not only the diffusion of organic food consumption, but also an increase in the number of organic farms. Having said that, due to the presence of certain constraints and barriers (for example changing price and availability) a quick transition into organic consumption-production cannot be expected. Government price control schemes to control minimum or maximum prices and trade control to balance exports and imports can speed up the demand side attempt to reduce the environmental impacts of production.

Recommendation 4:

Comparing the findings of classification and clustering, we notice in explaining purchasing behavior both methods give high importance to behavioral factors (including attitude, social norms, emotions, hedonic goals, habits) and shopping-drinking style (including purchasing and drinking frequency and the average expenditure for a bottle of wine) but not to the socio-demographic factors. Having said that, we would not realize the significance of product prices and the mixed effects of impulsive tendencies in provoking consumers to go against their intentions if we had only used one method. Therefore, we suggest future researchers dealing with heterogeneity in human behavior benefit from the strength of applying both methods, simultaneously.

Our findings have important implications for both theory and practice. From a theoretical perspective, they provide strong evidence for emphasizing the influence of hedonic, gain and normative cues as well as a dual role of emotions and impulsiveness in choosing organic products. We further argue that organic purchasing decisions are complex; relying only on planned behaviors and disregarding the presence of interruptive factors between intention and behavior, a comprehensive view over the decision-making process for organic food may not be captured. From a practical perspective, the results suggest that price is still an obstacle for purchasing organic food. In this sense, sales promotion and government subsidies on organic products can facilitate purchasing and at the same time, support habitual organic purchasing. Retailers can offer an organic section inside their stores specifically designed for different occasions to facilitate the behavior. Encouraging a greater sense of joy and positivity at the store and using social media, and target marketing to advertise the range of organic products can be other effective mechanisms to change wine purchasing behavior. Future research would benefit from examining the efficacy of the suggested interventions in shifting behavior towards organic consumption.

6.3. Suggestions for future work

The presented research involves the development of theories and methodologies for extending the SC to consider consumer behavior and preferences. However, more research is desired to more fully investigate the applicability and performance of ESSC framework in different industries. The future work can go in three specific directions as summarized below (see Figure 6.1).

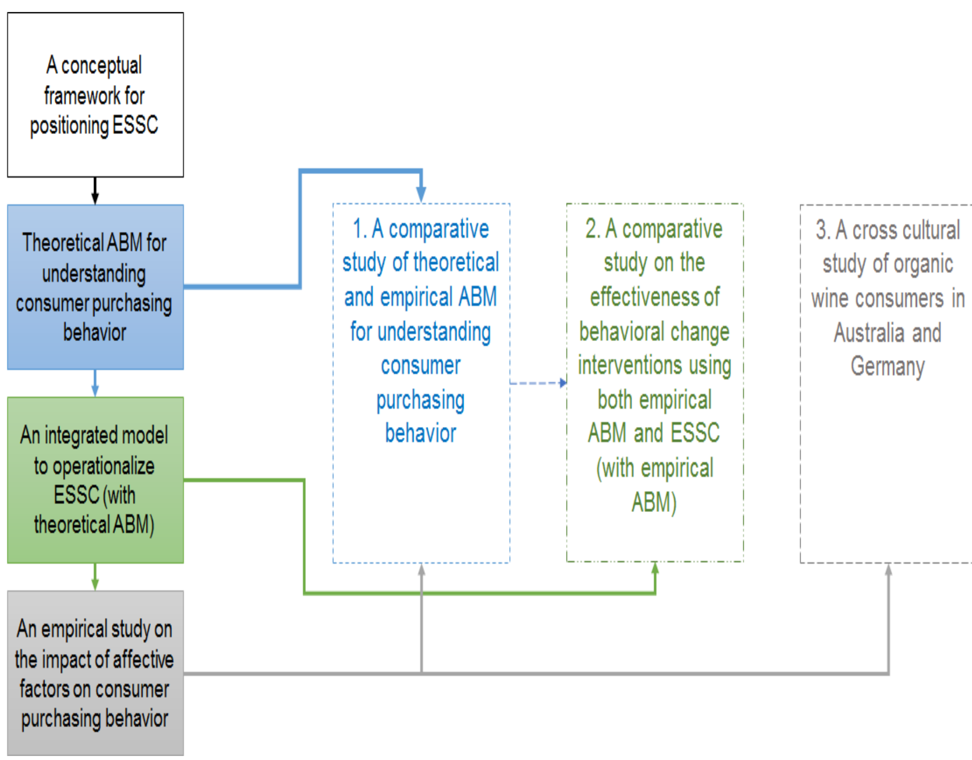


Figure 6.1. Future research areas

1. *A comparative study between theoretical and empirical ABM:* In ABM, both theory and data can inform the assumptions. Statistical methods such as regression and structural equation modeling are dominant methods in developing data-driven or empirical ABMs. Given the importance of designing a model that can simulate

the current consumer preferences as accurately as possible, the need for advancing the methods in this field is more visible. To ensure an accurate translation from observational data to computational models, we suggest the integration of machine learning algorithms in building empirical ABMs. As a case study, one may compare the outcomes of theoretical model, ORvin (Chapter 3) with an empirical ABM (using Chapter 5 predictive models) to assess the performance of theories in explaining consumers purchasing behavior for organic wine.

2. *A comparative study on the effectiveness of behavior change interventions:* We already tested the effectiveness of structural and persuasive interventions for changing behavior in ORvin. This model focused only on consumption-side and assumed a static and continuous production operations in the SC. However, in ESSC, we discussed the feedback between consumption and production and showed the complexity and dependencies in the supply-demand relationship. Thus, it is interesting to use the survey data (Chapter 5) for re-parametrizing ORvin (Chapter 3) and ESSC (Chapter 4), run exactly the same scenarios, and compare the results of interventions. This experiment can reveal the implications and importance of capturing comprehensive system view, like ESSC, for designing future policies.

A comparative study of consumer preferences for organic wine in Australia and Germany: This study examined consumer preference and consumption behavior of Australians with respect to organic wine (Chapter 5). We highlight the intention-behavior gap and attempt to explain it by investigating the role of affective and cognitive factors. As similar behavioral gaps in the German consumers for purchasing organic wine have been identified and explained, it would be worthwhile to make a comparison between the results of two studies and derive the similarity and difference among factors. The study may further discuss the generalizability of the empirical research results.

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