Systems thinking in managing the success of food products 2019 Andrijana Horvat

Systems thinking in managing the success of food products

Exploring the potential of a system dynamics approach

Andrijana Horvat

Propositions

1. Regardless of the multitude of available tools, the food industry still often relies on "trial and error" in new product development.
   (this thesis)
2. When it comes to improving food product success, there is a gap between what is known in science and what is implemented in food industry.
   (this thesis)
3. Every person is a modeller (Epstein, J. M., J Artif Soc S, 2008, 11, 12).
4. Developing interdisciplinary skills is strongly influenced by the kind of resources one has access to (Bridle, H., et al., Futures, 2013, 53, 22-32).
5. The current publishing and academic systems are a bottleneck for publishing interdisciplinary research.
6. Collecting an abundance of data may give a false perception of being in control.
7. Baking is just a more appetizing form of chemistry.

Propositions belonging to the thesis, entitled:
Systems thinking in managing the success of food products - Exploring the potential of a system dynamics approach
Andrijana Horvat
Wageningen, 29 August 2019

Systems thinking in
managing the success of food products
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Thesis

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Chapter 1

General introduction

1.1. The problem of high product failure rates

Development and launch of new products is an important activity in food processing companies. New products that become widely accepted by consumers contribute to profitability and growth of the company. However, developing and launching new products can be risky (Huang et al., 2015), since not all food products launched on the market experience a wide success among consumers. Product failures represent a serious financial loss for the company and a great deal of new product launches never achieve expected commercial success. According to a report of Nielsen, between the years 2011 and 2013, 76% of the launched consumer goods did not survive one year on the market, while 45% remained on the market for less than half a year (see Figure 1.1)(Dijksterhuis, 2016). New product failure has been a persisting problem, and not only specific to food industry. Castellion and Markham (2013) showed high and stable rates of new product failure in the period from 1965 to 2010 across various industries, with consumer goods industry having one of the highest failure rates of 45% on average.

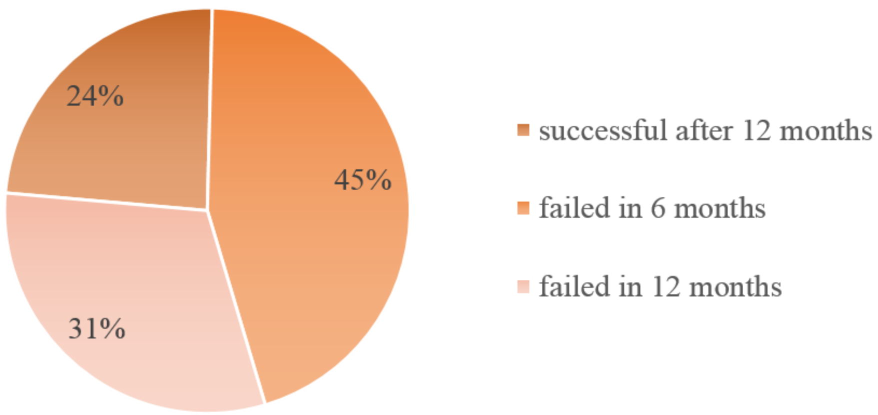

Figure 1.1. *Success and failure of consumer goods launched in Europe between the years 2011 and 2013 (The Nielsen Company, 2014).*

Since the 1960s, scientists have been attempting to understand how to make new products more successful (van Kleef, 2006). Today, despite more than half century of research, there is still no formula that would guarantee product success. Before 1960s, food companies used to rely on technological progress as the source of new product ideas (van Kleef, 2006). With the development of modern markets and the appearance of supermarkets with numerous products, a growing need for frequent product change and product differentiation from competition emerged as a main driver of new product development (NPD) (Earle et al., 2001). The ideas for product changes originated mainly from people responsible for product development, like marketing and R&D professionals. Since those strategies were not guaranteeing product success, in the last few decades, uncovering consumers' needs has become a starting point for developing successful products (Voulgari et al., 2013, van Kleef et al., 2005). According to Kressy (2014), product success lies in the middle of the three circles, i.e., technological feasibility, market viability, and consumer desirability (Figure 1.2). The product needs to be technologically feasible, or needs to be easily produced with technology the company possesses. It needs to be viable on the market, i.e., economic goals of the company need to be attainable on the market where the product is launched. The product also needs to be desirable to consumers by satisfying their needs and wishes. However, the problem of new product success is described in a simplified manner in Figure 1.2 and these three aspects represent a boundary of a complex system of interlinked factors and functions, which will be described in the following paragraphs.

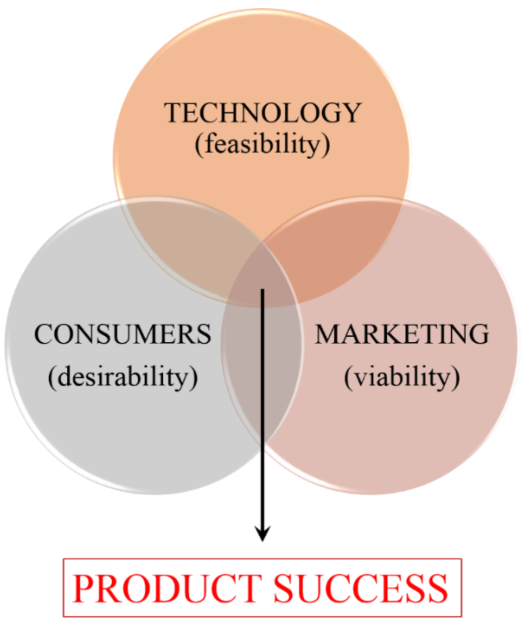

Figure 1.2. *Product success depends on technological feasibility, market viability, and consumer desirability (adapted from Kressy, 2014).*

1.2. Company functions involved in ensuring new food product success

Developing successful products requires cooperation of multiple company functions. There are three main functions directly involved in food product management: marketing experts, food technologists, and consumer researchers (van Trijp and Steenkamp, 2005) (see Figure 1.3). Marketing experts select which opportunities to exploit, tailor advertising, and weight products against the firm's values and benefits. Food technologists work towards realizing technological product characteristics and attributes. Consumer researchers work on identifying consumer opportunities and weight products attributes against consumers' needs (van Trijp and Steenkamp, 2005). However, sometimes companies do not have a separate consumer research function and this work is partially done by R&D professionals (e.g., sensory scientists) and marketing experts. The experts from three functions interact with many other firm functions, e.g., packaging, purchasing, sales, finance, legal, distribution etc. (Lehmann and Winer, 1997).

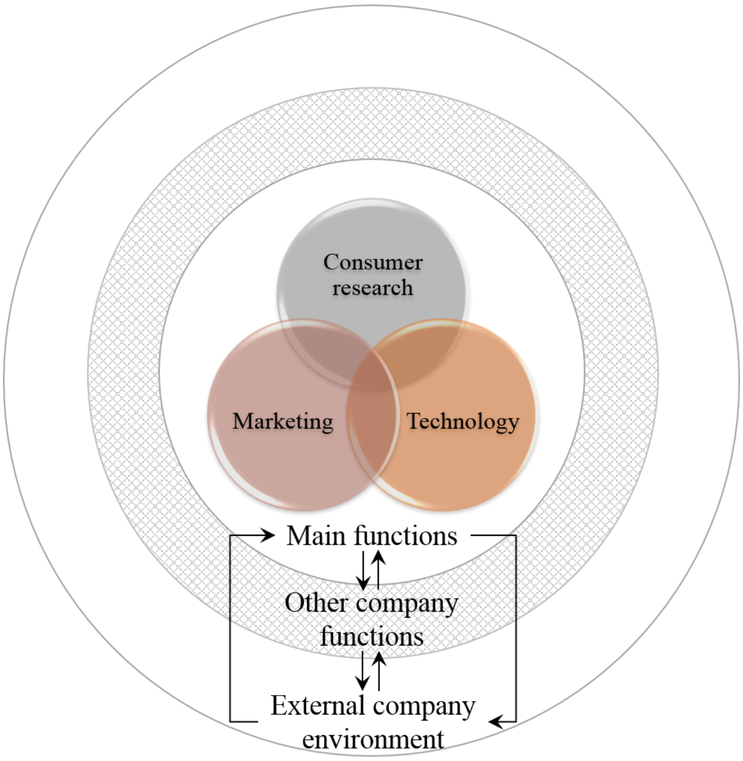

Figure 1.3. *A food company has three main functions involved in food product-related decision-making towards ensuring its success. In their decision-making, they need to communicate with other company functions and consider the environment outside of the company.*

Companies are operating in a complex external environment that is constantly changing (Earle et al., 2001). To have a better control over product's success, experts from the three functions need to adapt food products according to changes in the external environment (Earle et al., 2001) (see Figure 1.3). For example, marketing function needs to monitor the entrance of competitors on the market and adjust the marketing mix strategy accordingly. Technology experts need to keep up with technological innovations in the sphere of new ingredients and production processes. Consumer researchers need to keep track of consumer changes, which might affect the acceptance of existing products and of consumers' unfulfilled needs and wishes. To demonstrate that changes in the company's environment need to be considered by all three functions to assure product success, an example of the gluten-free food trend can be used. For example, consumer researchers would first need to perform consumer research to identify that consumers have a need for gluten free products and to learn of their expectations of such products. Technology experts would need to develop a gluten-free product, while having in mind consumers' wishes and technical feasibility. Finally, marketing experts would need to develop an advertising strategy to reach potential buyers of such products and adapt that strategy if, for example, competition enters the market.

Furthermore, companies affect the external environment as well. By launching certain products, they reinforce change in the environment. For example, if a company develops a novel gluten-free product, soon competitors might appear who will start launching similar products and the company will need to adapt their products to remain competitive on the market. This forms a feedback process where a company, by making certain decisions, causes environment to change and those changes in the environment, in turn, affect the company. Any decision of one actor may provoke reactions by others (Sterman, 2004). The company needs to consider these things (and many other) in the two main stages of product management: in the new product development and also once the product appears on the market, in the product life cycle (PLC).

1.3. New product development (NPD) and product life cycle (PLC)

Products usually go through the process called new product development (NPD) before appearing on the market. The NPD usually consists of four phases: opportunity identification, product development, product testing, and product launch (see Figure 1.4) (van Kleef et al., 2005; Urban and Hauser, 1993). If a product meets certain metrics in one NPD phase, it can move to another phase. This process-oriented approach to NPD is commonly called the stage-gate process (Straus, 2009). In the opportunity identification phase, product ideas are generated and screened, and the best market to enter is defined (Urban and Hauser, 1993). Here, the company strategy and objectives, legislation, technological opportunities, and actual consumers' needs all become factors in deciding whether an idea should progress through the NPD process (Luning and Marcelis, 2009). When the company identifies an attractive opportunity, the product design phase starts. Here, companies focus on translating consumers' needs into technological specifications of the physical product. This phase includes converting product ideas into specifications of physical products and development of product prototypes. Moreover, advertising and promotion campaigns, and marketing mix elements are developed. In the product testing phase, product, advertising, and introduction strategy can be tested on a test market, or in laboratory tests with consumers. If the final tests are successful, the product will be launched on the market and the product life-cycle management starts (Urban and Hauser, 1993).

In the product life-cycle (PLC), the company monitors product performance on the market, i.e., sales over time (Figure 1.5), to adapt the strategy and to assure profit. The PLC usually consists of four phases: introduction, growth, maturity, and decline (Figure 1.4). Introduction phase of the PLC involves building the demand for the product by extensive advertising and promotion. Figure 1.5 shows that in this phase the sales grow slowly and the profit is low due to high product introduction expenses. In the growth phase, the focus is on building efficiency of the production and marketing. Here, sales and profit grow because of increase in consumer acceptance of the product. In the maturity phase, sales growth slows down because of the decrease of interest by consumers and companies focus on strategies aimed at maintaining market share. In the decline phase, many consumers stop buying the product in favour of something newer and companies sometimes decide to exit the market (Kotler, 2003; Anderson & Zeithaml, 1984). On the other hand, companies can decide to revitalize or reposition the product for new markets to extend its life (Urban and Houser, 1993). In that case, the NPD phase can start again.

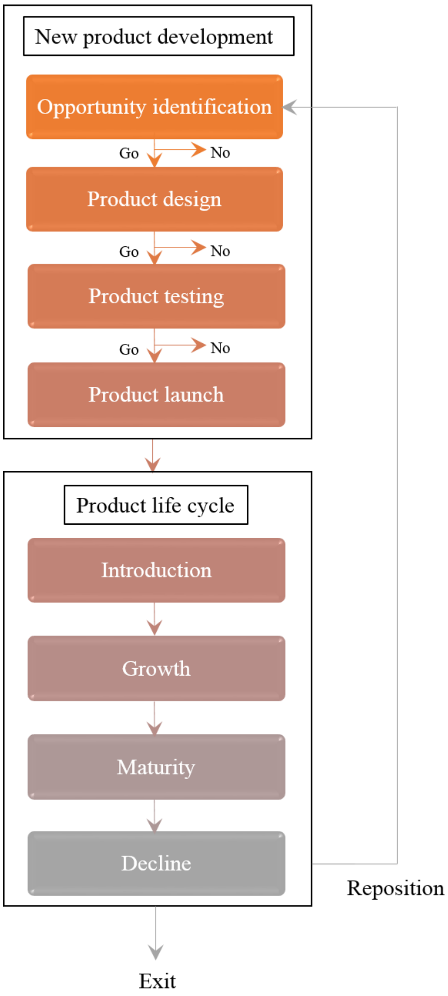

Figure 1.4. *Stages of food product management: new product development, followed by the product life cycle. Adapted from Urban and Hauser (1993).*

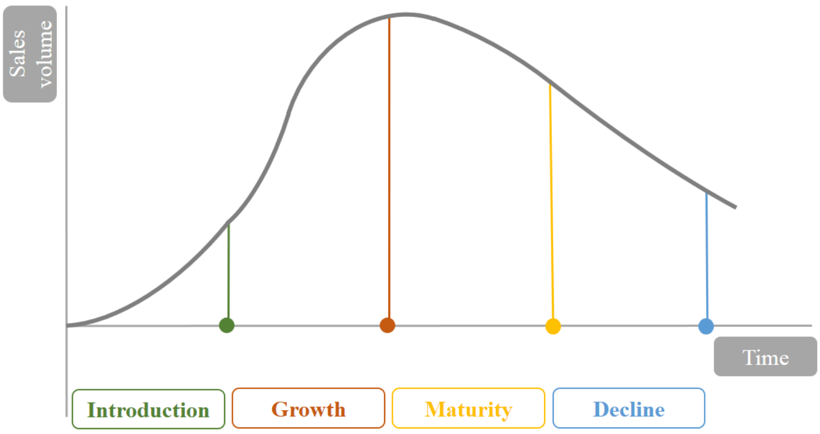

Figure 1.5. *Product's performance in the product life cycle (adapted from Weinstein (2002)).*

1.4. Need for an integrated approach to food product management

Product development is a complex process where a multitude of people need to consider numerous factors to assure product success, some of which are shown in Figure 1.6. A new food product consists of intrinsic and extrinsic product attributes (Figure 1.7). According to Luning and Marcelis (2009), intrinsic product attributes encompass safety (microbial, chemical, physical), health (nutritional value, health compounds), sensory (texture, taste, odour, colour), and convenience (easy to use). These attributes are variables that technology experts consider when developing new products. Moreover, current state of the processing technology in the firm is another important variable for technology function, which can influence intrinsic product attributes (Kaul and Rao, 1995).

On the other hand, marketing function makes decisions about extrinsic product attributes, such as communication about specific intrinsic product attributes to consumers (Luning and Marcelis, 2009). Moreover, some extrinsic product attributes may be communicated only if a certain technology has been applied (e.g., organic, sustainable products), while others are independent of the applied technology (e.g., brand name). Lastly, marketing function makes decisions related to other marketing mix variables, apart from product attributes, i.e., price, promotion, and product distribution (Kaul and Rao, 1995).

Consumer research function's role is to understand if and why consumers choose a certain product. Consumers make their choice based on their preferences, which are formed based on perceived product attributes. Perceived product attributes are formed jointly by the levels of intrinsic and extrinsic product attributes, and marketing mix (Grunert, 2002; Kaul and Rao, 1995). Moreover, consumers' choice and perceptions are also affected by consumers' individual characteristic and situational factors (e.g., time and money constraints, product availability). Since consumers' decisions have a direct impact on product success (e.g., product sales), the role of consumer function in NPD is to collect information about consumers' needs and preferences, which can be translated into product characteristics by technology and marketing function. Furthermore, once the new product prototype is developed, the consumer function also needs to assess the extent to which the developed prototype satisfies consumers.

Consumer decision-making process is a central concern of consumer-oriented new product development (Busse and Siebert, 2018, Grunert and van Trijp, 2014). A successful consumer-oriented new product development requires a balanced input from technology, marketing, and consumer researchers throughout the development process. Consumer understanding should be an integral part of all the stages of NPD (Grunert and van Trijp, 2014). This integrated way to consumer-oriented NPD is a challenging task, which requires a close interaction between the three functions (Grunert and van Trijp, 2014). Moreover, since consumers' needs change over time, there is a need to understand how those changes affect consumer acceptance of a product during PLC (Grunert and van Trijp, 2014).

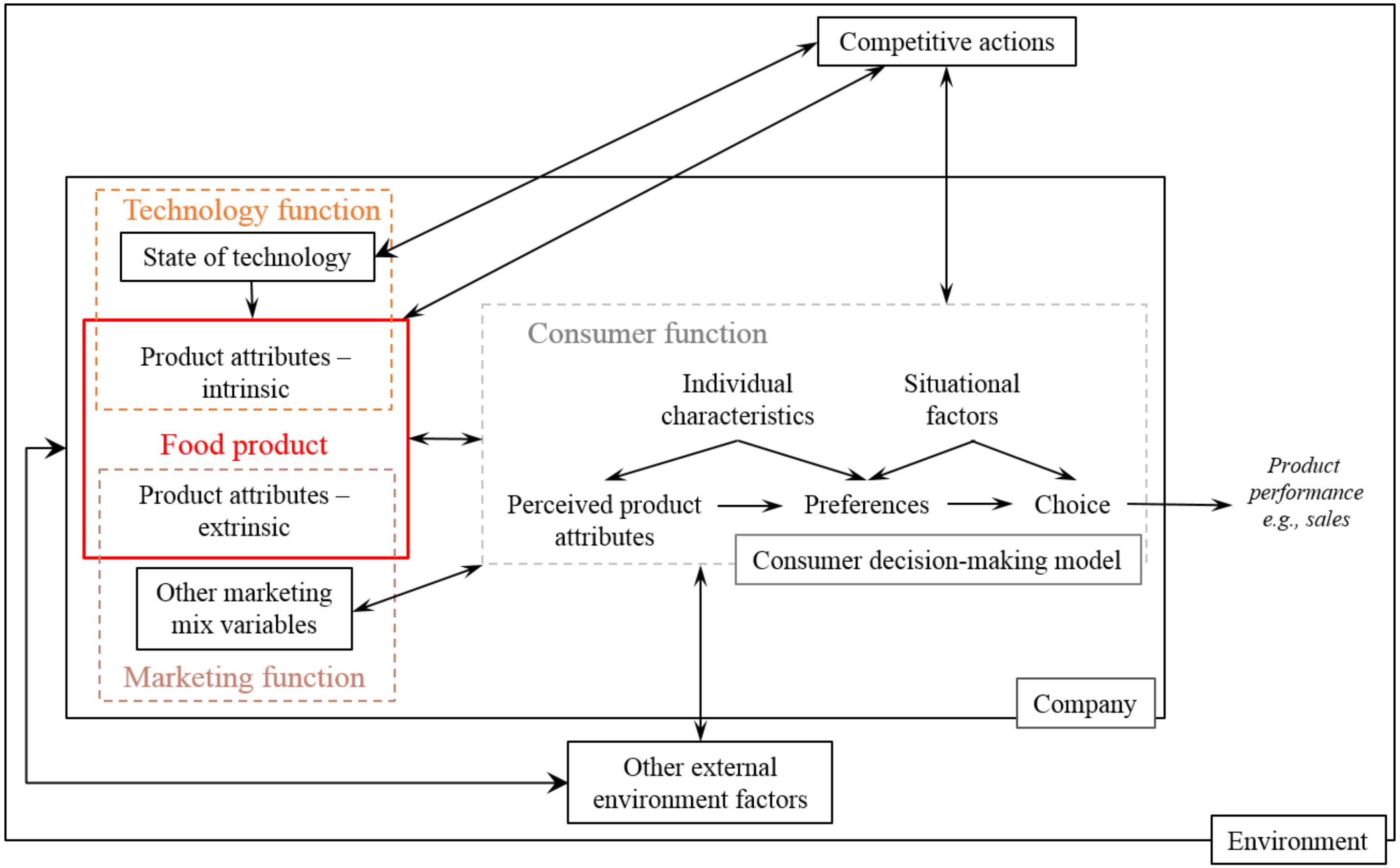

Figure 1.6. *Framework showing different factors that the three functions (technology, marketing, and consumer research) need to consider when developing new food products (adapted from Kaul and Rao (1995)).*

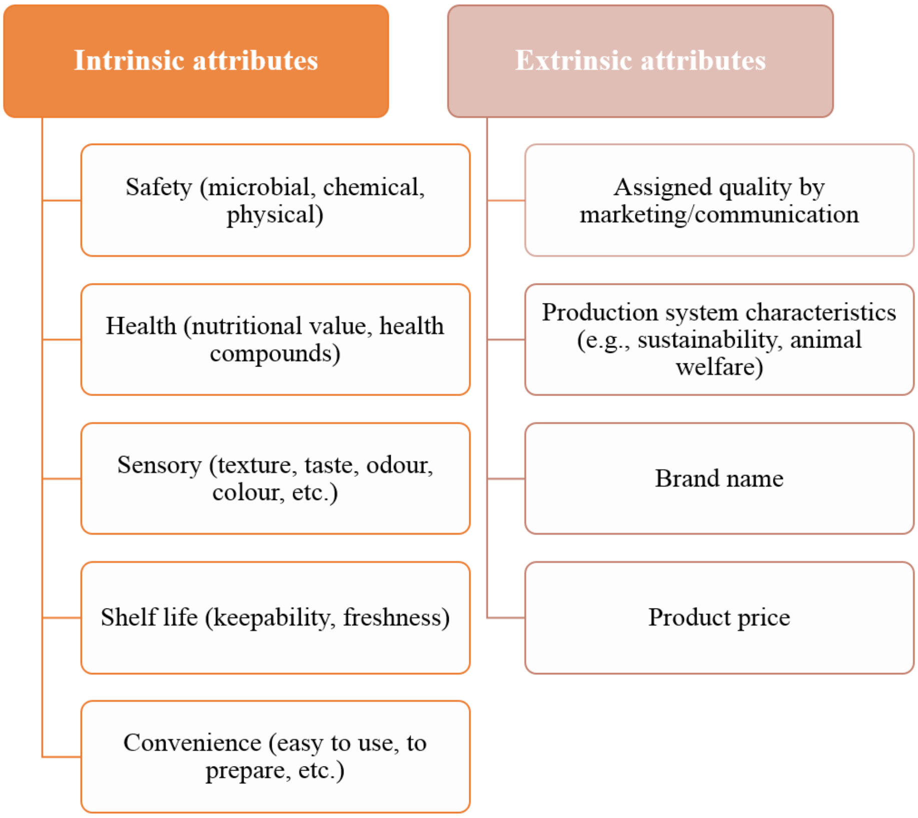

Figure 1.7. *Some intrinsic and extrinsic food product attributes (modified from Luning and Marcelis, 2009).*

1.5. From linear process-oriented approach to cyclical goal-based approach to food product success

The existing literature shows NPD and the PLC as linear processes, which is visible in Figure 1.4. The process in Figure 1.4 resembles the linear stage-gate process, which has been advocated as a way to successfully perform activities in food product development (Grunert and van Trijp, 2014; Moskowitz et al., 2009). However, phases in NPD are not necessarily sequential and some stages might overlap (Voulgari et al, 2013). Moreover, it is usually not so easy to determine in what PLC phase the product is (Cao and Folan, 2012). Therefore, going through the process in a sequence of activities might not be the solution for every company. In such situations, a goal and objective-based approach can be used. In this approach, instead of dictating a set of steps, goals that are essential to product success are defined and the whole company, and in particular the three main NPD functions, work towards fulfilling the goals (Straus, 2009). One example of the goal and objective-based approach is an integrated approach to product development proposed by Moskowitz et al. (2009).

In this approach, there are six goals that a company needs to reach to assure product success:

- define and meet consumers' needs and expectations;
- the food product itself needs to perform in terms of taste and use;
- the packaging needs to be appropriate;
- good name, positioning and advertising is required;
- the product needs to be consistent with corporate strengths or financial goals.

These are all important goals to achieve in NPD, which affect product sales in the PLC.

However, this integrated approach to food NPD does not take into account two important things: the change in consumers' needs over time and other changes in the company's environment. Those changes require food companies to respond to them by changing their product, in order to maintain successful product sales. However, this might lead to even more change in the environment (Figure 1.3). This feedback perspective to reaching company's goals is opposed to the common linear way of perceiving decision-making in NPD and the PLC, which is depicted in Figures 1.8 and 1.9.

Figure 1.8 shows that if there is a problem with a product, it means that there is a discrepancy between the actual product performance and the goal performance. This problem can be related to NPD discrepancy between products' current sensory quality and the goal sensory quality. It can also be related to the PLC discrepancy between current sales and expected sales. In the linear way of thinking, there is an assumption that after a decision on how to solve the discrepancy was made, certain actions will be undertaken, which should lead to improved performance (Morecroft, 2010). This type of problem solving assumes that each problem is an isolated event (Morecroft, 2010). However, Figure 1.6 explicitly shows that all the company functions and the company's environment are interrelated. Therefore, the actual problem-solving situation should look more like the one in Figure 1.9. An action aimed at improving performance of one function could affect performance of another function. To go even further, any action might provoke a reaction from other actors in the environment.

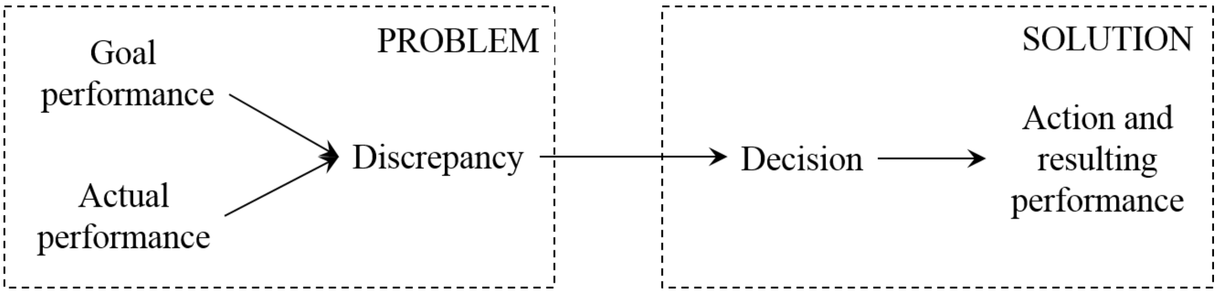

Figure 1.8. *Linear perspective to problem solving (adapted from Morecroft (2010)).*

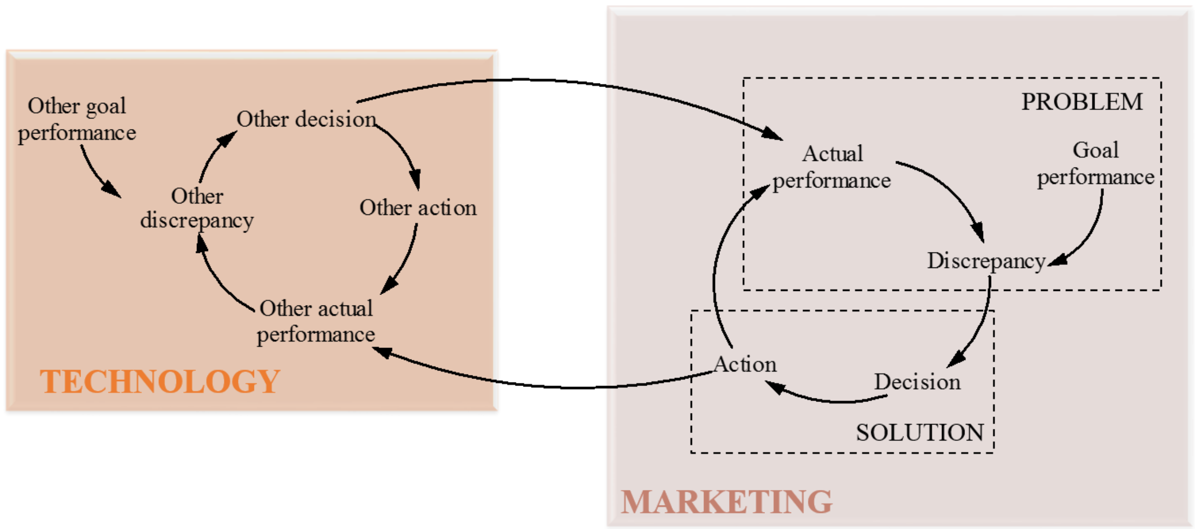

Figure 1.9. *Feedback perspective to problem solving (adapted from Morecroft (2010)).*

Taking a feedback perspective on food product performance requires a mind shift, which might not be easy for the existing management in food firms (Morecroft, 2010). Instead of merely focusing on actions that need to be taken to solve a problem, it is important to understand what side effects could appear due to the particular action. For example, a problem of low sales could be solved by decreasing the product price, but only for a while. A side effect of lowering the product price could be that competitors lower the price of their products as well, which would bring sales to its previous state (Sterman, 2004). Another example is development of product alternatives that are similar to existing company's products to respond to food trends, for example salt reduction. With an increased interest of consumers for a product with reduced salt, their satisfaction with the regular product might decrease.

1.6. Systems thinking and system dynamics to study feedback processes affecting product success

To identify feedback processes that are important in achieving product success, systems thinking approach can be employed. Systems thinking is an approach to problem solving based on "seeing wholes, recognizing patterns and interrelationships, and learning how to structure those interrelationships in more effective, efficient ways" (Senge and Lannon-Kim, cited in Mella, 2012, pg. 8). A system, from a systems thinking perspective, is considered to consist of interconnected elements, which serve a common goal (Dekkers, 2015). Systems thinking goes beyond the linear "problem-solution" structure. The linear way of solving problems is not taking into account the whole picture, the entire time span of the problem. Solutions to problems, although in the short run favourable, merely shift the problem from one part of the system structure to another, and in the end, the problem returns and can even grow bigger (Senge, 1990). An example is incorporation of palm oil in food products, which has been used as an alternative to other fats that contain unhealthy trans-fat. The use of palm oil has immediate positive impacts from a technological perspective. However, due to the long-term negative impact of palm oil on environment, many consumers started avoiding products containing this ingredient (Boehm et al., 2010). Systems thinking, therefore, suggests finding the cyclical causes and effects of the problem, i.e., feedback loops. The representation of systems thinking approach comes in the form of qualitative causal models, i.e., causal loop diagrams (e.g., Sterman 2004) and means-criteria diagrams (e.g., Enserink et al., 2010). Qualitative causal models are useful to describe the problem under study, to deepen the knowledge about it, and to identify causes and effects of actions undertaken to solve the problem (Olaya and Gomez-Quintero, 2016; Sterman, 2004). However, they are not able to show the emergent dynamic behaviour of the system. Nevertheless, qualitative causal maps are a valuable input for developing quantitative simulation models, such as stock and flow system dynamics (SD) models (see Figure 1.10), which can reveal emergent dynamic behaviour of a system.

System dynamics is a methodology to study dynamic complex problems, which involve the notion of feedback (Richardson and Pugh III, 1981). SD models contain integral equations, which can be depicted with stock and flow diagrams (SFD) (see Figure 1.10) (Sterman, 2004; Richardson and Pugh III, 1981). The behaviour of stocks in SFDs is defined by the following equation:

$$s(t) = s(t_0) + \int_{t_0}^{t} f(t) - g(t)dt, \qquad \text{Eq. 1.1}$$

where (t) is a stock at time t, $s(t_0)$ is the initial value of this stock, $f(t)$ is an inflow and $g(t)$ is an outflow. Other types of elements in SFDs are auxiliary variables and parameters. The main sources of dynamics in SD models are reinforcing and balancing feedback loops (Sterman, 2004; Richardson and Pugh III, 1981), which affect flows and lead to changes in stocks. SD models contain numerus integral equations, which makes it difficult to solve them analytically, and software such as Vensim or iThink is used.

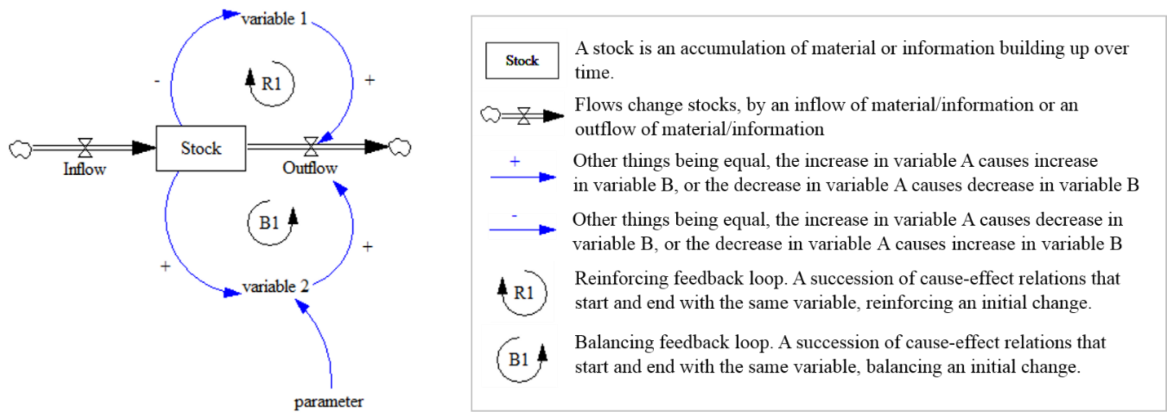

Figure 1.10. *Elements of a stock and flow diagram.*

SD models are descriptive models useful to study patterns of behaviour or graphs of variables over time (such as the PLC sales curve) and not for point prediction (Barlas, 2009; Sterman, 2004; Ford, 1999). First, to study the dynamic behaviour, the problem needs to be formalized. When building an SD model of a specific problem, one focuses on variables that can explain the problem's behaviour over time. By undertaking this approach, one aims at studying "dynamic complexity" of the problem, instead of "detail complexity". In other words, instead of identifying a large number of variables relevant for the problem (i.e., detail complexity), the focus is on variables that form feedback loops. After building an SD model of a particular problem, the model can be used to study how changes in its structure and parameters affect the emergent dynamic behaviour. The changes in the model should imitate different decisions that can be made in the real word. Experimenting with the model helps in gaining new insight into the problem and it improves decision-making (Forrester, 1962). Building and simulating an SD model could enable experimentation with different decisions related to improving product success in a safe virtual environment on a computer, instead of conducting experiments in the real world. Although SD models are not the only modelling and simulation approach appropriate for studying complex dynamic problems (e.g., agent-based modelling can be used to study complex dynamic problems), the power of SD models is in their "clear and consistent presentation of the assumptions" (Grösser, 2013, pg. 53). In the past, SD approach has been successfully applied to study some food-related issues: advertising of generic dairy products (Nicholson and Kaiser; 2008), the influence of ripeness of fruit at the point of sales on profit (Schepers and van Kooten; 2006), and the influence of carbon-labelling of milk on consumer purchase behaviour (Zhao and Zhong, 2015). However, such SD models have not yet been used to investigate complexity of new food product performance in NPD and PLC by integrating the three functions: technology, marketing and consumer research.

1.7. Problem formulation and objective of the thesis

The development of new food products has been a major driver of growth for food industry. However, the complex nature of food NPD and PLC has presented a challenge amongst food companies in ensuring success of new food products. Given the multitude of actors participating in decision-making in establishing product characteristics, and the dynamic nature of product performance, there is a need for an approach that would capture the dynamic and complex nature of food product success, and which would facilitate decision-making to increase product success chances. Systems thinking and system dynamics are approaches that allow identification of feedback processes relevant to understand dynamic aspects of food product success, while taking into account perspectives of multiple actors. However, these approaches have not yet been employed to unfold dynamic complexity of food product success and to integrate perspectives of three main functions responsible for food product success in NPD and PLC: technology, marketing, and consumer research. Therefore, this thesis aims at developing qualitative and quantitative systems thinking and system dynamics models. They could provide insight into dynamic feedback processes relevant for understanding food product performance throughout the PLC, from the perspective of different functions participating in NPD and PLC. The focus of each study is on increasing understanding of consumer food choice from dynamic perspective.

1.8. Outline of the thesis

Chapter 1 provides general information about the challenges of assuring new food product success, the complexity of the food products and the processes in NPD and the PLC, and the main functions in food companies responsible for food product success. Moreover, we justify the need to understand feedback processes contributing to product performance and to employ systems thinking and system dynamics.

To understand to what extent current practices in food industry support the exploration of dynamic complexity of food product performance, Chapter 2 focuses on studying the types of data and methods that food companies employ. Due to the importance of consumer-oriented approach to food product development, we study to what extent European food companies use three types of consumer data, i.e., consumer involvement, food trends, and environment factors data in different NPD and PLC phases and what data collection methods companies employ. I examine if the type of data used is affected by the function, the size of the company, and the type of NPD project. Moreover, I explore if European food companies employ modelling and simulation methods.

In Chapter 3, I review literature on new product performance to understand what factors and what feedback processes are important to assess performance of a new food product during its life cycle, from the perspective of three functions: marketing, technology, and consumer research. I present the findings of the structured literature review in the form of causal maps, i.e., means-criteria diagrams, which contain lagging and leading performance indicators. Finally, the findings are synthesized in an integrated framework for dynamic assessment of performance of a new food product.

In Chapter 4, I demonstrate the development of a system dynamics model on a case study of insect-based food adoption in the Netherlands. The model was developed based on a structured review of literature on edible insects, on the innovation of diffusion paradigm and on the Bass diffusion system dynamics model. I use the developed model to discuss the potential of system dynamics modelling and simulation in understanding the adoption of radical new food, and to indicate knowledge gaps that need to be addressed to increase understanding of this problem.

Chapter 5 focuses on the development of a system dynamics model with a group of stakeholders from a food company. I demonstrate the use of system dynamics to structure and understand a complex dynamic problem of stagnating sales of a healthy snack product through a series of group model building sessions. Moreover, I explore the usefulness of the group model building in improving team-collaboration in solving a complex dynamic problem in the PLC.

In Chapter 6, I present a general discussion of the findings, concluding remarks on the extent to which objective of the study was achieved, and recommendations for further research.

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Chapter 2

Understanding consumer data use in new product development and the product life cycle in European food firms – an empirical study

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Abstract

New food products have a high chance of market failure. To improve the chances of new product success, a consumer-oriented approach to product development has been recommended. The approach emphasizes the importance of an optimal fit between consumers' needs and the new product. To achieve this goal, food professionals generate and use various consumer data types and methods. However, very few studies address the extent to which the food industry uses consumer data in product development. This study investigated to what extent European food firms use various consumer data in different phases, i.e., new product development (NPD) and the product life cycle (PLC) and what data collection methods they employ. The current study classified consumer data into three types: consumer involvement, food trend, and environmental factor data. The results showed that more than 85% of the respondents use all three data types in NPD, while they rarely use consumer data in the PLC. Respondents most frequently use data collection methods such as focus groups, consumer surveys, and indirect data collection (e.g., internet, magazines). These methods are less effective in assuring product success and in developing new to the world products. In fact, more than half of the respondents never or rarely worked on new to the world projects. Increasing the use of consumer data in the PLC and adapting data collection methods to the type of the project and the phase of product development present opportunities for food firms to improve chances of new product success.

1. Introduction

Failure of new food products is still a prevailing end-result of many firms' product development activities. Nielsen reported that between 2011 and 2013, 76% of the launched consumer goods did not survive one year on the market, while 45% remained on the market for less than half a year (Dijksterhuis, 2016). In the last few decades, firms have been applying a consumer-oriented, or consumer-led, approach to product development to design successful new food products. Busse and Siebert (2018) provided an extensive overview of definitions for consumer-oriented and consumer-led product development. Here, we adopt the description of consumer-oriented product development as achieving an optimal degree of fit between the new product and consumers' needs (Costa and Jongen, 2006).

To determine the optimal degree of fit between the new product and the needs of the target consumers, food firms use various methods to collect data about consumers' needs and preferences (Busse and Siebert, 2018; Nijssen and Lieshout, 1995). According to Moskowitz and Saguy (2013), a range of tests to obtain consumers' response to product ideas, concepts, and physical products to assess a product's acceptance level have been employed in the food industry (Moskowitz and Saguy, 2013). These tests have been useful for obtaining *consumer involvement data* (Janssen and Dankbaar, 2008). Other types of data can also be used to determine the optimal degree of fit, such as data on current *food trends* or aggregated data on *environmental factors* that affect consumers' needs and preferences, e.g., demographic, economic, socio-cultural, or technological (Janssen and Dankbaar, 2008; Stewart-Knox and Mitchell, 2003; Grunert et al., 1996). However, the majority of related scientific literature is focused on what consumer involvement data firms employ and what data collection methods they use, while the other two consumer data types, i.e., food trends and environmental factors, have rarely been studied (e.g., Busse and Siebert, 2018; Geyer et al., 2018; Creusen et al., 2013; Janssen and Dankbaar, 2008; Kaulio, 1998). Data obtained by direct consumer involvement in NPD, such as consumer co-creation, can be a source of product ideas and can have a positive effect on the financial performance of a company (Zaborek and Mazur, 2019; Martinez, 2014). However, it is also important to understand whether food firms use food trend and environmental factor data. Such data indicate future changes in consumers' needs and preferences, which can aid product success by developing products with longer product life cycles (PLC) (Fuller, 2005).

In this study, we define product development as the combination of NPD, which includes the development phases before a new product is launched on the market, and the PLC, which includes the phases after the new product is launched on the market. Past studies mainly focused on consumer involvement data obtained and used in the new product development (NPD) up to the launch of new products. However, consumers' needs and tastes change over time and the degree of fit is not static, which is why firms often redesign and reformulate food products once they are already on the market (van Trijp and Steenkamp, 2005; Urban and Hauser, 1993). To successfully redesign and reformulate a product, it is essential to know what consumers like, or dislike, about the existing product (Otto and Wood, 2003). Moreover, previous studies analysed consumer data use of firms from various industries, not only food firms, except, for example, the study by Janssen and Dankbaar (2008). Therefore, it is necessary to understand whether food firms obtain and employ consumer data after the product is launched during the PLC

Moskowitz and Saguy (2013) called for redefining the role of consumer research in food companies. They suggested that consumer research should move beyond mere product testing and become more involved in other business issues in product development. To achieve that, there is a need to increase scientific knowledge (Moskowitz and Saguy, 2013). The success of products in the PLC is one of the most important business issues since product sales substantially contribute to company growth (Barczak and Kahn, 2012). A potential way consumer research could become more involved in business issues could be by generating and using consumer data beyond product testing in NPD. Currently, it is not well known to what extent food firms use different types of consumer data in NPD or if they employ it after products are launched in various PLC phases. Therefore, there is a need to assess the current situation in the food industry and to identify knowledge gaps in consumer data use. This could facilitate the generation of scientific knowledge that would allow broader use of consumer research in assuring product success. Therefore, the aim of the current study is to contribute to the understanding of what consumer data types European food firms employ, in what phases of product development they use the data, and how they collect the data.

Based on the study aims, the overall research question follows:

What consumer data types do people working in product development in European food firms use in NPD and the PLC, in what phases of NPD and the PLC do they use it, and what consumer data collection methods do they employ?

To answer this research question, we developed a conceptual framework containing the types of consumer data used in product development as the basis for the survey design, which we distributed among European NPD professionals working in food firms.

2. Conceptual framework

To analyse what consumer data types firms use during product development, we developed a conceptual framework (Figure 2.1). The framework displays three main data types, i.e., consumer involvement, food trend, and environmental factor data. In the context of this study, the three data types are independent of each other, and we differentiate them based on their specificity and time frame. Moreover, Figure 2.1 shows that we aim to determine whether the phase of product development, the type of product development project, and the firm size and function influence the types of consumer data used. The framework was developed based on a review of literature on product development, with specific focus consumer involvement, food trends and environmental factor data. We explain the framework elements, as outcomes of the review, in the following text.

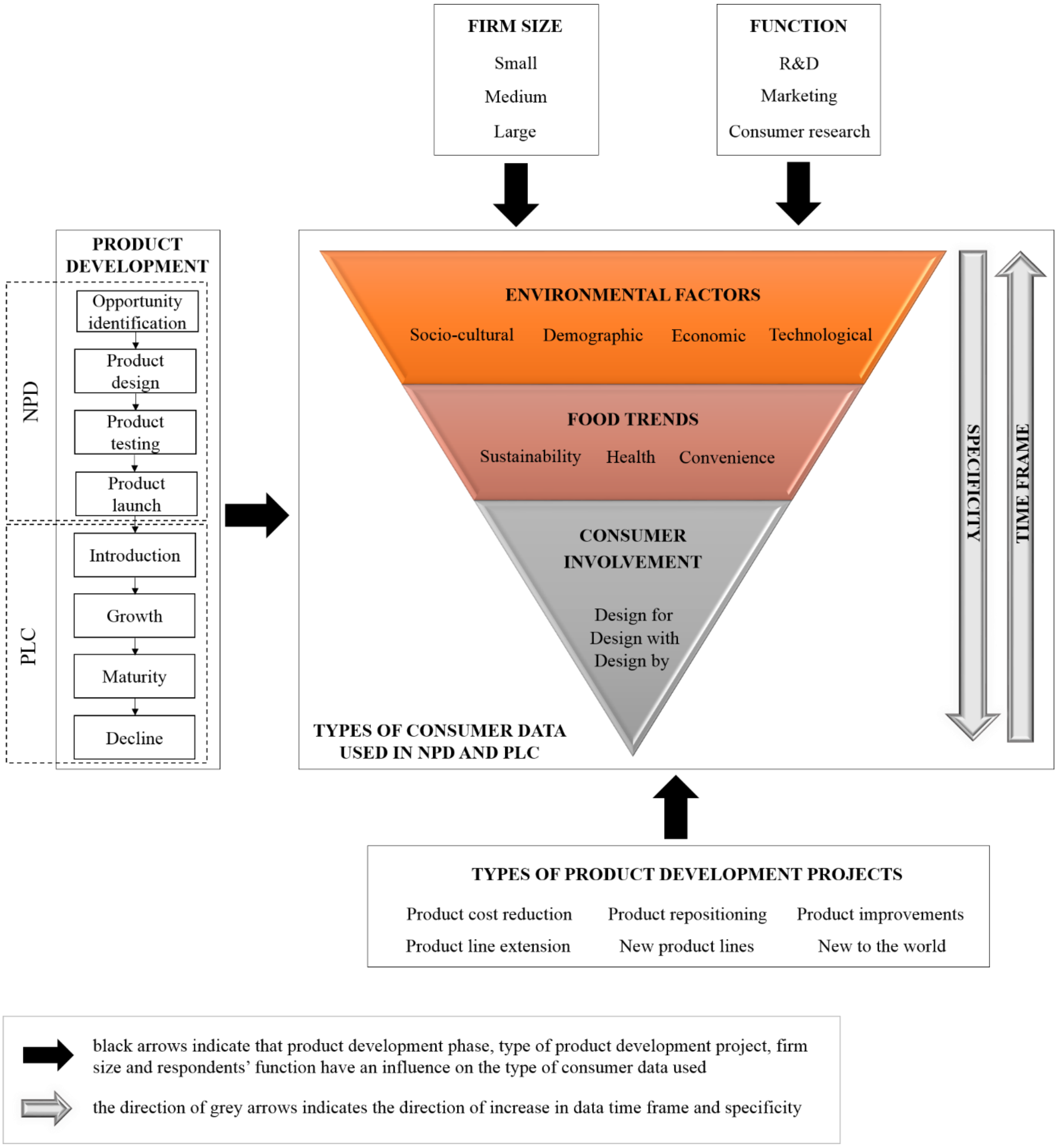

Figure 2.1. *Conceptual framework for analysis of the use of three consumer data types, i.e., consumer involvement, food trends, and environmental factors. It is hypothesized that the type of consumer data used can vary based on the phase of product development, the type of product development project, the firm's size, and the function of the respondent.*

2.1. Types of consumer data

2.1.1. Consumer involvement data

Interaction and collaboration with consumers are major aspects of consumer-oriented NPD that are important for understanding the fit of the product with consumers' needs (Costa and Jongen, 2006). The most straightforward way to assess the degree of fit between a new product and consumers' needs is to involve consumers directly in the NPD and the PLC. Here, we consider three major consumer involvement levels to obtain data: "design for", "design with", and "design by" (Janssen and Dankbaar, 2008; Kaulio, 1998). In the "design for" level, consumers' needs and preferences are determined based on general theories and models of consumer behaviour and on information obtained from the internet, magazines, marketing agencies, supermarkets, consumer surveys, and focus groups. In the "design with" level, consumers typically express their opinions on product concepts and physical products through sensory tests, concept testing, conjoint analysis, and category appraisal. In the "design by" level of involvement, consumers are strongly and actively involved and participate in the co-creation of the product, and methods such as lead user method, innovation templates, and consumer-idealized design are employed. Consumer involvement, such as with the "design by" level, is beneficial for the development of unique product ideas due to the use of methods that allow the discovery of consumer needs and values of which consumers themselves are not aware (Janssen and Dankbaar, 2008; Kristensson et al., 2003). However, "design by" methods can have certain limitations that hinder their more frequent use compared to "design for" and "design with" methods. For example, the lead-user method requires a dedicated team of 4 to 6 people with advanced interviewing skills for part-time work for six months to develop a product concept (Eisenberg, 2011). Likewise, consumer-idealised design, although similar to focus groups, requires skilful facilitators and more time investment by facilitators and participants (Ciccantelli and Magidson, 1993). While some studies show that employing "design by" methods, such as co-creation and lead user method, results in successful NPD (Zaborek and Mazur, 2019; Chang and Taylor, 2016), there is a lack of empirical evidence, which would show that the use of "design by" consumer involvement, instead of "design for" or "design with", will lead to more successful products.

2.1.2. Food trend data

To generate strong product ideas and to ensure that products remain competitive on the market, firms can monitor food trends to observe changing consumers' needs (Stewart-Knox and Mitchell, 2003; Davis, 1993). Consumer data collected at the beginning of the project can be years older in the moment of product launch, depending on the duration of NPD. Therefore, food professionals need to develop products for their future consumers (Fuller, 2005). Market research firms deliver information about future trends in food consumption to food firms. Food professionals can use such data throughout product development to eliminate short-lived fads and to invest in products that correspond to long-lasting trends (Fuller, 2005).

In the last few decades, three major food trends have been at the forefront of food innovations, which are included in the framework. First, the healthy food trend includes foods that support people's healthy food lifestyles, e.g., superfood, functional foods, the "free from" trend, clean label, sugar or calorie reduced, natural, and less processed foods (Asioli et al., 2017; Bugge, 2015). Second, convenience food products help consumers minimize the time and effort required for food preparation, consumption, and clean up (Jackson and Viehoff, 2016; Brunner et al., 2010), e.g., food in small package units, ready-to-eat, and ready-to-cook food. Third, sustainable products contribute to economic, social, and environmental goals in the food chain, e.g., vegetarian, vegan, ethical, local products, or those with a claim of special origin (Grunert et al., 2014; Vermeir and Verbeke, 2006).

2.1.3. Environmental factor data

On a more aggregated level, change in consumers' needs can be explained by four categories of environmental factor data: 1) socio-cultural; 2) demographic; 3) economic; and 4) technological (van Trijp and Steenkamp, 2005; Meulenberg and Viaene, 2001). In the following text, we explain the impact of some factors on changing consumer needs.

Socio-cultural factors include changes in consumers' attitudes, lifestyles, education, ethnicities, and buying patterns, which result from urbanisation and globalization. Urbanization has led to the emergence of lifestyles based on speed, movement, and convenience. Processed convenience foods have replaced raw products and seasonal food consumption disappeared, leading to changes in buying patterns (Costa and Jongen, 2006; Meulenberg and Viaene, 2001). Furthermore, the level of education has increased, leading to the appearance of environmentally and nutrition-conscious consumers (Kearney, 2010; Brody and Lord, 2007; Costa and Jongen, 2006; Senauer et al., 1991). Furthermore, globalization has brought different cultures closer (Cwiertka, 2005; Ehrenfeld, 2003), causing changes in ethnic and religious composition in cities and changes in food habits of both local and new populations (Wandel et al., 2008; Cwiertka, 2005). All of this has been playing a role in shaping consumers' attitudes by affecting their evaluation of a product over time (Solomon, 2008).

Demographic factors, such as population growth, age, sex distribution, household size, and regional migration, are also indicators of food demand (Hoek et al., 2004). For example, the ageing population tends to have a higher demand for healthy food (Costa and Jongen, 2010; Senauer et al., 1991), while primarily female consumers buy organic food (Padel and Foster, 2005; Davies et al., 1995). A decrease in the size of families and households led to demand for convenience food that can be prepared simply and quickly (Costa and Jongen, 2006; Meulenberg and Viaene, 2001; Senauer et al., 1991). Finally, increased mobility resulted in more regional migration, which led to increased food supply variety (Meulenberg and Viaene, 2001).

Economic factors, such as disposable income, unemployment levels, price fluctuations, and the macroeconomic situation, indicate consumers' buying behaviour (Senauer et al., 1991). Rising income can be an indicator of improvement in the quality of diets and food availability, but it can also lead to unhealthy diets high in fat (Kearney, 2010; Marmot, 2002), while lower income leads to limited consumption of fruits, vegetables, lean meat, and fresh fish (Drewnowski and Darmon, 2005; Nestle et al., 1998).

Technological advancement data relates to the technology used to produce a product. Although not directly obtained from consumers, this type of data is also an indicator of potential future change in consumers' needs (Ronteltap, 2007). Past technological advancements, such as ready-to-eat meals, meat alternatives, advances in packaging methods, and more nutritious food, have led to multiple innovations that changed consumers' preferences (Neville et al., 2017; Elzerman et al., 2013; Falguera, 2012; Elzerman et al., 2011; Costa and Jongen, 2010; Ozdemir and Floros, 2004). By following technological advancements in and outside of the food industry, companies can innovate by recognizing unfulfilled consumers' needs on the market (Jongen and Meulenberg, 2005). Technological innovation can create added consumer value, which can have a positive effect on product success (Kock et al., 2011).

2.1.4. Differences among data types – time frame and specificity

Figure 2.1 includes two dimensions (time frame and specificity), which we used to differentiate consumer data types. The time frame represents the relative length of the period in which consumer data are obtained. Consumer involvement data represent the shortest time frame, as it usually involves data collection at one point in time, e.g., sensory tests (Delarue and Boutrolle, 2010; Poretta et al., 2010). Sensory tests can be designed as controlled laboratory studies that aim to measure consumer evaluation of sensory attributes of the product, or there can be an attempt to capture a realistic consumption setting, with the aim of measuring the overall consumer preference and acceptance of the product (Hemmerling and Spiller, 2016). Food trends indicate a change in attitudes over time, leading to a change in consumption patterns (Grunert, 2005). Determining consumption patterns requires data collection over a few weeks, months, or years and includes food balance sheets, retail sales, and household budget surveys (Kearney, 2010). On the other hand, strategic environmental factors require the collection of data over many years to observe patterns of change. For example, projection of demographic data can be made up to 10 or 20 years (Senauer et al., 1991).

The second dimension of Figure 2.1 refers to data specificity. Here, we look at data specificity as relating to a particular product. In that sense, strategic environmental factors are the least specific because they provide general information not related to a specific product (e.g., Kearney, 2010; Lundahl, 2006; Fuller, 2005; Senauer et al., 1991). This type of data can be used for various product development projects. Food trend data are more specific since they contain detailed information about certain consumer groups and their interest in particular types of products (e.g., Mintel Ltd., 2018). Lastly, consumer involvement data offer the most specificity because they are usually obtained during the development of a specific product, which is tested or developed with consumers (e.g., Janssen and Dankbaar, 2008; Kaulio, 1998).

2.2. The product development phase, type of product development project, firm size and respondent's function can impact consumer data use

Figure 2.1 implies that various consumer data types can be used to a varying extent in different product development phases due to specific activities in each phase. NPD typically consists of four phases: opportunity identification, product design, product testing, and product launch (van Kleef et al., 2005). Throughout those phases, consumer data are used to narrow down multiple product ideas and to develop and test new product concepts and formulations to assure product success (Luning and Marcelis, 2009; van Kleef et al., 2005). The PLC also typically consists of 4 phases: introduction, growth, maturity, and decline. Here, consumer data facilitate developing market strategy while the product goes from being unknown to consumers, to a product with a well-established consumer demand, until consumers stop buying it in favour of something newer (Fuller, 2005).

According to Earle et al. (2001), there are six types of product development projects: product cost reduction, product repositioning, product improvements, product line extension, new product lines, and new-to-the-world products. The type of innovation project can dictate the consumer data type needed. For example, new-to-the-world projects can benefit from direct consumer involvement data to refine product concepts and physical products and to develop effective communication strategies when the product is unfamiliar to consumers (Janssen and Dankbaar, 2008; Earle et al., 2001). However, there is a lack of empirical evidence comparing the use of different consumer involvement data and their contribution to product success.

Finally, firm size and respondents' function could affect the type of data used. Small and medium firms exhibit financial constraints compared to large firms, which can lead to fewer resources available for obtaining consumer data (Beck and Demirguc-Kunt, 2006). Moreover, the difference in consumer data used can arise from respondents having different functions based on respondents' different tasks. Three functions are central to consumer-oriented product development. R&D, marketing, and consumer research (Costa and Jongen, 2006; van Trijp and Steenkamp, 2005). R&D's focus is on delivering superior technology to consumers, while marketing focuses on product positioning and image building (van Trijp and Steenkamp, 2005). Consumer research provides an in-depth understanding of consumers' needs, the translation of those needs into product requirements, and consumer product testing (Moskowitz and Saguy, 2013). The conceptual framework is the basis for the survey design.

3. Materials and methods

3.1. Online questionnaire

3.1.1. Questionnaire design

The questionnaire, consisting of three sections, was designed according to the principles laid out by Iarossi (2006). The first section included general questions aiming at typifying the respondents (e.g., if they work in food product development, their function, firm size) and the type of food innovation projects they are involved in. The second and the third section reflected the structure of the conceptual framework. Here, we aimed to collect answers on the data types that respondents use in NPD and the PLC and in which particular phases of NPD and the PLC. Finally, respondents indicated how data were collected by selecting various methods. The questionnaire (see Supplementary material 1) was pretested by pilot administration, after which some minor changes were made. Cronbach's alpha value of 0.948 indicates that reliability was assured (Lance et al., 2006).

3.1.2. Respondents

Potential respondents were approached at the Anuga Food Fair (2017) in Cologne (Germany), via LinkedIn, and through the authors' personal networks. They were asked to complete an online survey via the SurveyMonkey platform. Eligible respondents needed to work in a European food producing firm and needed to be directly involved in the new product development process in that firm, i.e., as marketing, R&D, or consumer research personnel. Most of the respondents were from different companies. In some cases, respondents came from the same company (e.g., a marketing and an R&D expert from the same company). The survey was open throughout October and November 2017. In total, 202 responses were collected. The final sample size consisted of 113 respondents, as 89 respondents did not reply to all mandatory questions. The final survey sample is described in Table 2.1.

Table 2.1. *Description of the final survey sample*

Category	Number of respondents	Percentage (%)
Firm size		
Small	19	16.8
Medium	25	22.1
Large	69	61.1
TOTAL	113	100
Respondent function		
R&D	73	64.6
Marketing	34	30.1
Consumer research	6	5.3
TOTAL	113	100

3.2. Data analysis

All statistical analyses were performed using IBM SPSS Statistics Version 23. Descriptive statistics were performed to determine the frequencies of respondents' replies regarding the use of consumer involvement, trends, and environmental factors and other collected data. McNemar's test was performed to assess the difference between percentages of different consumer data types used in NPD and the PLC. Pearson's chi-square test of independence was performed to examine the association between the size of the company and the type of consumer data used, the phase of NPD and the PLC in which data are used, and the data collection methods employed. Moreover, the association between the function of the respondent and the type of consumer data used, the phase of NPD and the PLC in which data are used, and the data collection methods employed were examined. Finally, the association between the project type and consumer data used in NPD and the PLC was tested. If a significant relationship was observed, a post hoc cellwise adjusted residual method (see Supplementary material 1) was performed to examine independence between the categories of firm size, function, and projects. Bonferroni correction to the p-value of 0.05 was employed (MacDonald and Gardner, 2000).

4. Results

4.1. Consumer data types used in product development

Table 2.2 shows the frequency of use of different consumer data types during new product development (NPD) and the product life cycle (PLC). All three major data types are used to a similar extent in NPD, i.e., for direct consumer involvement, food trend, and environmental factor data frequency of use was 85.8%, 87.6%, and 89.4%, respectively. The results of McNemar's test suggest that all consumer data types are significantly less frequently used in the PLC than in NPD.

Table 2.2. *Frequency of use of various categories of consumer involvement, food trend, and environmental factor data in new product development (NPD) and the product life cycle (PLC) and results of McNemar's test to assess the difference between percentages of different consumer data types used in NPD and the PLC.*

	Phase of product's life			
Type of consumer data used	**NPD (% respondents)**	**PLC (% respondents)**	χ^2	**p-value***
Consumer involvement	***85.8***	***50.4***	*33.33*	*<0.001*
"design for"	79.6	45.1	31.04	*<0.001*
"design with"	73.5	33.6	36.82	*<0.001*
"design by"	31.1	13.3	12.50	*<0.001*
Food trends	***87.6***	***54.9***	*31.84*	*<0.001*
healthy	74.0	41.6	30.42	*<0.001*
sustainable	61.0	33.6	24.50	*<0.001*
convenience	50.0	24.8	22.35	*<0.001*
Environmental factors	***89.4***	***63.7***	*21.78*	*<0.001*
socio-cultural	83.2	61.1	16.89	*<0.001*
demographic	73.5	48.7	21.78	*<0.001*
economic	66.4	46.0	16.03	*<0.001*
technological	63.7	40.7	18.78	*<0.001*

degrees of freedom = 1
*p-value significant below 0.05

Respondents most frequently use consumer involvement data in NPD from the "design for" and "design with" category, while only 1/3 of the respondents employ the "design by" data. The use of all three categories of consumer involvement data is significantly lower in the PLC.

Moreover, the trend towards healthy food is the most frequently incorporated trend in NPD (74%), followed by convenience (61%) and sustainable food (50%). In the PLC, respondents most frequently use data on healthy food trends (41.6%), while sustainability and convenience trend data are less often used (33.6% and 24.8%, respectively).

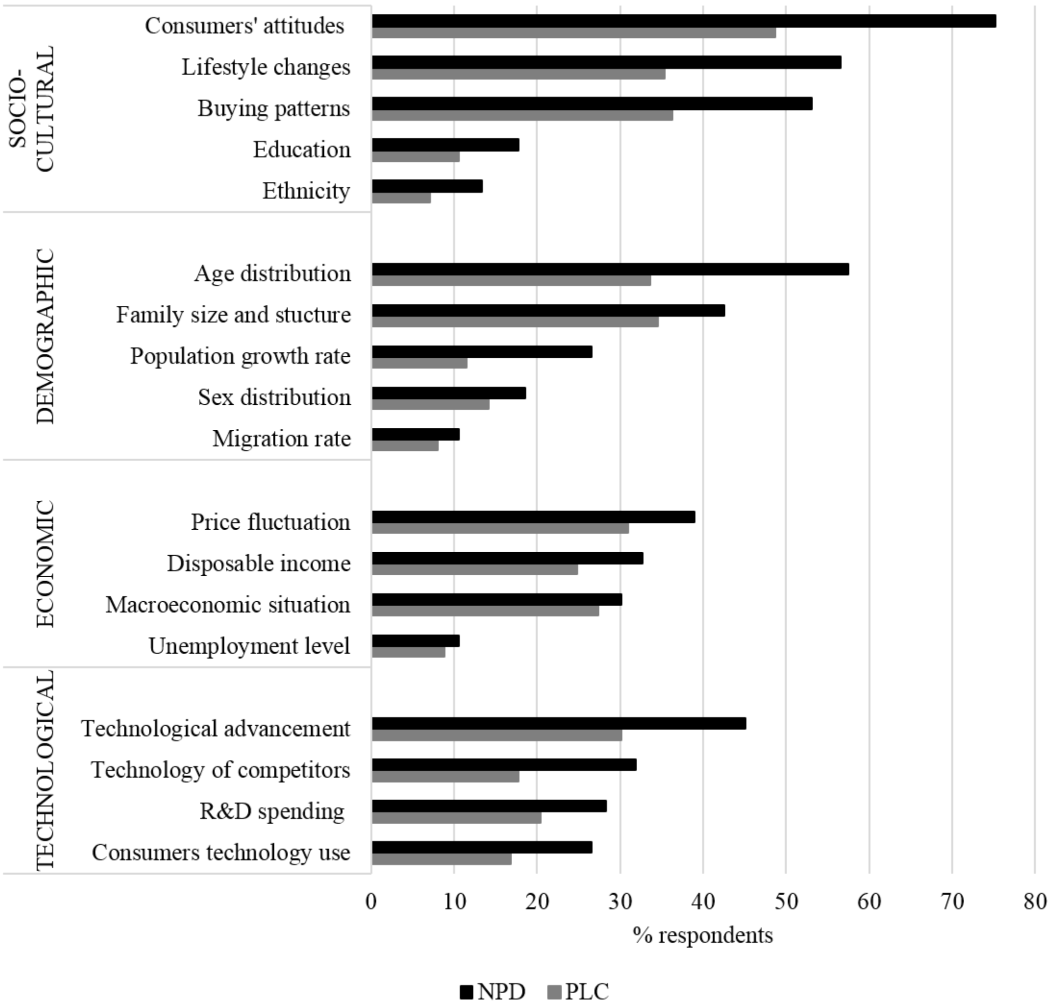

Figure 2.2. *Frequency of use of various environmental factors (socio-cultural, demographic, economic, and technological) in new product development (NPD) and the product life cycle (PLC).*

Figure 2.2 shows the frequency of the use of environmental factors, i.e., socio-cultural, demographic, economic, and technological, in NPD and the PLC. Overall, socio-cultural factors are the most widely used, followed by demographic, economic, and technological factors. In the category of socio-cultural factors, most respondents use information about consumers' attitudes towards product quality in NPD, as well as in the PLC (75% and 49%, respectively). Within the demographic factors, the age distribution of the population and the family size and structure are the most commonly used factors. Among economic factors, 39% and 31% of respondents use price fluctuation data in NPD and the PLC, respectively. Within the group of technological factors, respondents most frequently use data about technological advancement in their field in NPD (45%) and the PLC (30%).

4.2. Use of consumer data in different phases of product development

Figure 2.3 shows that respondents use all three consumer data types the most frequently in the opportunity identification and product design phases of NPD. In the product testing phase, the use of consumer involvement data remains more prevalent than the other two data types. Figure 2.3 indicates that approximately a third of the respondents use consumer involvement, food trend, and environmental factor data in the introduction phase of the PLC, with environmental factors being the most frequently employed data type (41.6%). The utilization of consumer data further drops in the later phases of the PLC; approximately less than one quarter of the respondents use each of the three data types in the phases from growth to decline.

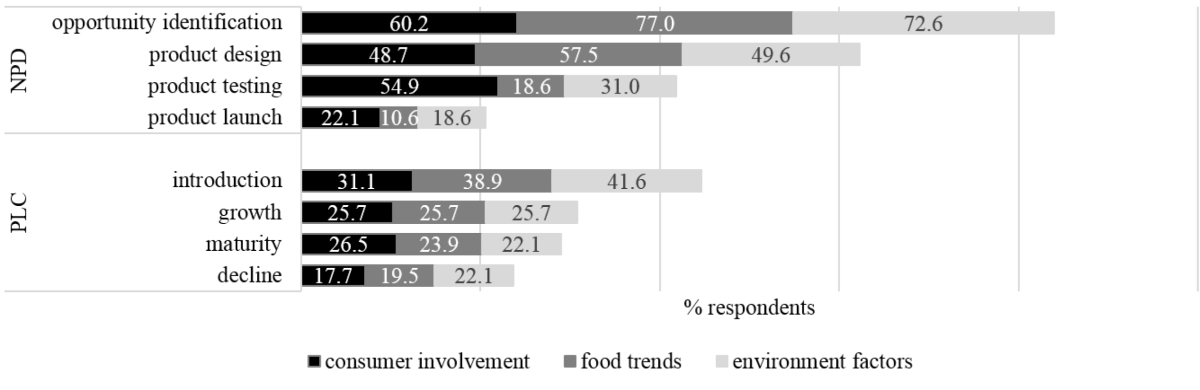

Figure 2.3. *Frequency of use of the three data types in various phases of new product development (NPD) and the product life cycle (PLC).*

4.3. Utilization of different methods to collect consumer data

Respondents use various methods to acquire consumer involvement data. Figure 2.4 shows that respondents frequently collect “design for” data through external sources, such as supermarkets, marketing agencies, the internet, and magazines. Consumers are most often directly involved through focus groups, consumer surveys, and sensory and concept testing. Interestingly, Figure 2.4 shows that only 50% and 61% of the respondents obtain consumer involvement data by product concept and sensory testing, respectively, with consumers. Moreover, according to Figure 2.4, the respondents in our study rarely use “design by” methods, such as the lead-user method and consumer co-creation.

Figure 2.5 shows the methods respondents use to collect food trend and environmental factor data. The internet (65%), e.g., specialized websites, and food fairs (62%) are the main channels of collecting food trend data. Furthermore, more than half of the respondents reported using newsletters and reports. The internet (57%) and consultancy firms (52%) represent the most commonly used sources of data on environmental factors. Moreover, most of the respondents do not use modelling and simulation methods during product development. The results showed that 70.8% of respondents use no modelling and simulation. Out of all the respondents who use some type of modelling, 84.8% employ statistical modelling, 5.3% use agent-based, 2.7% use system dynamics, and 1.8% employ discrete event modelling.

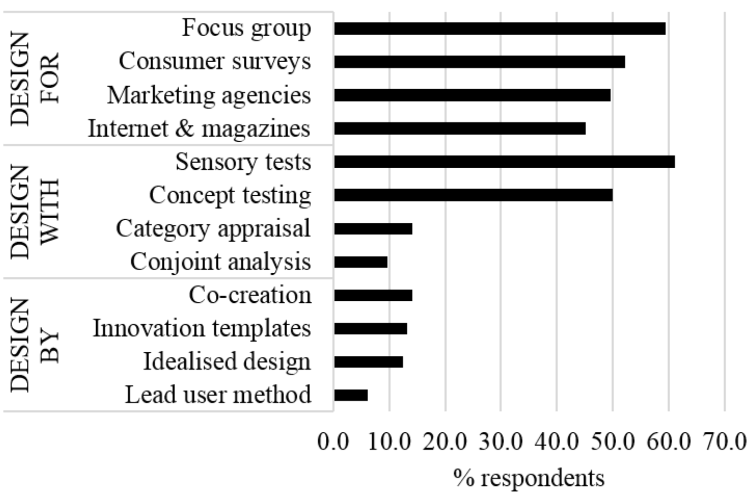

Figure 2.4. *The use of the common “design for”, “design with”, and “design by” methods of consumer involvement in European food firms.*

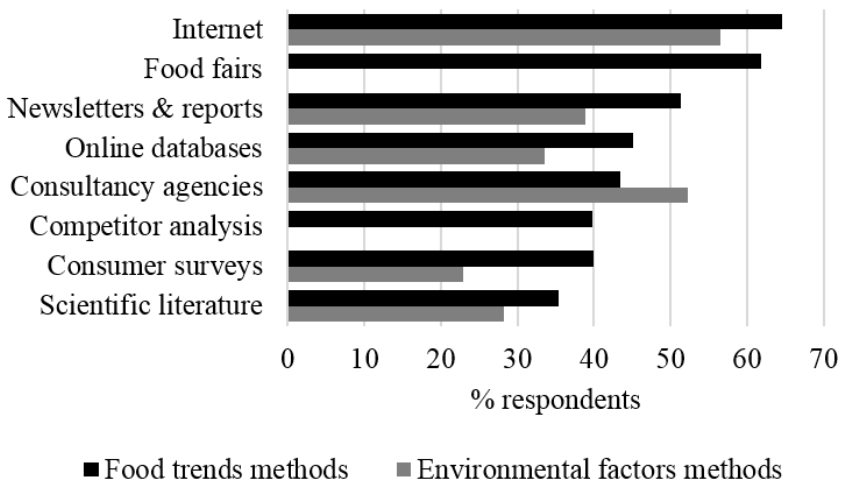

Figure 2.5. *Methods respondents use most frequently to collect data on food trends and environmental factors.*

4.4. Types of product development projects and relationships between project type and consumer data used

Figure 2.6 shows the frequency with which respondents work on the six types of NPD projects: product cost reduction, product repositioning, product improvements, product line extension, new product lines, and new to the world products. Product improvements and product line extension are the main types of product innovation projects among respondents, with 69.9% and 69% of respondents working on them often or always, respectively, followed by new product lines (62%) and product cost reduction (43%). Respondents engage the least frequently in new-to-the-world projects. Table 2.3 shows significant relationships between project types and consumer data used. A significant relationship was observed between the use of “design by” and healthy and convenience food trend data in NPD and participating in new to the world projects. There is also a relationship between respondents who often participate in new product line projects and who use economic and technological environmental factor data in NPD. Moreover, a relationship between always participating in product line extension projects and the use of economic factor data in the PLC was observed. Respondents who often participate in product improvements more often use consumer involvement and sustainable food trend data in NPD. Lastly, there is a relationship between sometimes participating in product repositioning and product cost reduction projects and the use of healthy and sustainable food trend data.

Table 2.3. *Results of the cellwise adjusted residual method, showing the relationship between the project type and consumer data use in NPD and the PLC (only significant relationships are shown).*

Association tested	Adjusted Z-score	χ^2	p-value*
New to the world projects			
Often participate in new to the world projects x Use “design by” consumer involvement data in NPD	3.28	10.76	0.001
Rarely participate in new to the world projects x Use “design by” consumer involvement data in NPD	3.64	13.25	<0.001
Always participate in new to the world projects x Use healthy food trend data in NPD	3.08	9.49	0.002
Often participate in new to the world projects x Use healthy food trend data in NPD	3.34	11.16	<0.001
Rarely participate in new to the world projects x Use convenience food trend data in NPD	5.51	30.36	<0.001
New product lines			
Often participate in new product lines projects x Use economic environmental factor data in NPD	5.14	26.42	<0.001
Often participate in new product lines projects x Use technological environmental factor data in NPD	3.42	11.70	<0.001
Sometimes participate in new product lines projects x Use sustainable food trend data in the PLC	4.80	23.04	<0.001
Product line extension			
Always participate in product line extensions projects x Use environmental factor data in the PLC	4.37	19.10	<0.001
Always participate in product line extensions projects x Use economic environmental factor data in the PLC	4.72	22.28	<0.001
Product improvements			
Often participate in product improvements projects x Use consumer involvement data in NPD	3.06	9.36	0.002
Often participate in product improvements projects x Use sustainable food trend data in NPD	7.28	53.00	<0.001
Product repositioning			
Sometimes participate in product repositioning projects x Use healthy food trend data in NPD	4.78	22.85	<0.001
Product cost reduction			
Sometimes participate in product cost reduction projects x Use sustainable food trend data in the PLC	3.32	11.02	0.001

*Bonferroni corrected p-value significant below 0.004
degrees of freedom = 1

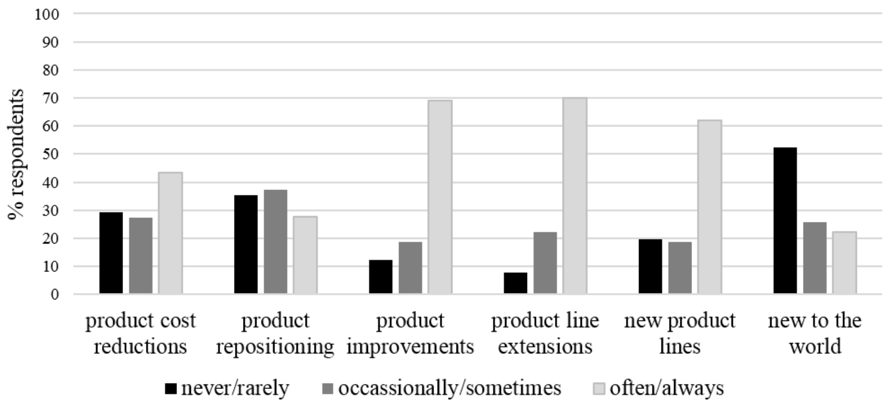

Figure 2.6. *Frequency with which respondents work on the six major types of product development projects.*

4.5. Relationship between firm size or function of the respondents and consumer data and methods used

Table 2.4 shows that respondents from large firms use consumer involvement data in NPD significantly more often, and specifically in the product testing phase, opposed to respondents from small companies. Respondents from large companies use consumer involvement methods, such as focus groups, consumer surveys, concept testing, and sensory tests significantly more frequently. Moreover, respondents from large companies use consultancy and marketing agencies to obtain trends and environmental factor data significantly more often. No significant association between the firm size and the data used in the PLC was observed. Table 2.5 shows that respondents with roles in marketing employ environmental factor data in the introduction phase of the PLC significantly more often. Furthermore, R&D personnel use scientific literature to obtain data on food trends more often.

Table 2.4. *Results of the cellwise adjusted residual method, showing the relationship between the specific firm size categories (small, medium, large) and consumer data use in NPD and between methods used. The table only shows results where a significant relationship was observed.*

Significant survey answer	**Adjusted Z-score**	χ^2	**p - value***
CONSUMER DATA USE IN NPD			
Small companies			
Do not use consumer involvement data in NPD	3.11	9.67	0.002
Do not use “design with” consumer involvement data in NPD	2.80	7.84	0.005
Do not use data on family size and structure (demographic environmental factor) in NPD	3.09	9.55	0.002
Do not use consumer involvement data in the testing phase of NPD	2.70	7.29	0.007
Large companies			
Use consumer involvement data in NPD	3.19	10.18	0.001
Use “design for” consumer involvement data in NPD	3.40	11.56	0.001
Use “design with” consumer involvement data in NPD	3.60	12.96	<0.001
Use consumer involvement data in the testing phase of NPD	3.90	15.21	<0.001
METHODS TO OBTAIN CONSUMER INVOLVEMENT DATA			
Small companies			
Do not use sensory tests to obtain consumer involvement data	2.89	8.35	0.004
Medium companies			
Use the focus group method to obtain consumer involvement data	3.15	9.92	0.002
Large companies			
Use the focus group method to obtain consumer involvement data	4.35	18.92	<0.001
Use survey methods to obtain consumer involvement data	2.69	7.24	0.007
Use concept testing to obtain consumer involvement data	2.95	8.70	0.003
Use sensory tests to obtain consumer involvement data	4.30	18.49	<0.001
METHODS TO OBTAIN FOOD TREND DATA			
Large companies			
Use consultancy and marketing agencies to obtain data on food trends	3.53	12.46	<0.001
METHODS TO OBTAIN ENVIRONMENTAL FACTOR DATA			
Small companies			
Do not use consultancy and marketing agencies to obtain data on environmental factors	2.98	8.88	0.003
Large companies			
Use consultancy and marketing agencies to obtain data on environmental factors	3.47	12.04	0.001

*Bonferroni corrected p-value significant below 0.008
degrees of freedom = 1

Table 2.5. *Results of the cellwise adjusted residual method, showing the relationship between the respondents' function (R&D, marketing, consumer research) and consumer data use in NPD and the PLC and between methods used. The table only shows results where a significant relationship was observed.*

Significant survey answer	Function	Adjusted Z-score	χ^2	p-value*
CONSUMER DATA USE IN NPD				
Do not use data on convenience food trend in NPD	R&D	2.65	7.02	0.008
Use data on the economic environmental factor unemployment level in NPD	Consumer r.	3.22	10.37	0.001
Use environmental factor data in the introduction phase of the PLC	Marketing	2.85	8.12	0.004
METHODS TO OBTAIN CONSUMER DATA				
Use scientific literature to obtain data on food trends	R&D	2.95	8.70	0.003

*Bonferroni corrected p-value significant below 0.008
degrees of freedom = 1

5. Discussion

In this study, we aimed to increase the understanding of what types of consumer data European food firms employ, in what phases of product development they use the data, and how they collect the data. The results were used to discuss the opportunities for improvement of data use in product development.

5.1. Use of different consumer data types: opportunities for improvement

Respondents use all three types of consumer data in product development (Table 2.2). From the category of *consumer involvement data*, "design by" data are less frequently employed. The lower frequency of use of "design by" consumer involvement data is in alignment with the observation that respondents rarely work on new to the world projects (see Figure 2.6). "Design by" level of consumer involvement is more often used in the NPD of new to the world projects, where it is important to discover unfulfilled consumer needs compared to existing products. "Design for" and "design with" data are more frequently used in NPD of incremental innovations, such as product improvement and product line extensions (Janssen and Dankbaar, 2008). Respondents rarely use "design for" and "design with" data in the PLC. Collecting consumer data in the PLC is essential to uncover the need to reposition a product or to start a new product line (Plewa, 2016; Earle et al., 2001; Urban and Hauser, 1993). The low use of consumer involvement data in the PLC (Table 2.2) may hinder firms' ability to uncover changes in consumers' needs and to recognize needs for product improvements and product line extensions.

Firms frequently use *data on food trends* in NPD (Table 2.2), which might be a successful strategy. Implementing insights from food trends into new products or product modifications could positively affect product success by fulfilling consumers' needs (Stewart-Knox and Mitchell, 2003; Davis, 1993). The high prevalence of the use of healthy food trend data could be an indication that firms are responding to consumers' health needs, which result from an increase in health issues, such as obesity and an ageing population (Yanovski, 2017; Nielsen, 2016). However, firms should not disregard the potential of other trends. For example, consumers are becoming increasingly aware of the impact food production has on the environment, leading to increasing demand for organic, natural, and local products (Rana and Paul, 2017; McGill, 2009; Aertsens et al., 2009; Vermeir and Verbeke, 2006). This could be an indication of the further growth of the sustainable food trend.

In the group of *environmental factor data*, only approximately half of the respondents use socio-cultural and demographic factor data in NPD, such as age distribution, lifestyle changes, and buying patterns, while other factors are used even less frequently, especially in the PLC (Figure 2.2, Table 2.2). This type of data can be valuable for distinguishing consumer segments and for developing product communication strategies, which can have a positive influence on a product's success (Nie and Zepeda, 2011; Lin, 2002). By understanding consumers' lifestyles, e.g., how people do things, behave, and what their habits are, food firms can capture consumers' psychological profiles (Nie and Zepeda, 2011). Since not all respondents use such data, this is something firms could take into account when choosing what environmental factor data to collect.

Data such as the education level of a population, migration rate, and ethnicity of a population are less frequently used (Figure 2.2) and opportunities to develop successful products could lie in more frequent use of those environmental factor data. It can be especially beneficial to anticipate demographic transitions occurring in markets in developing countries, as they can be predictors of changes in lifestyles and attitudes (Ali et al., 2010). Since these factors do not change substantially over time, monitoring them can be an opportunity for firms to anticipate long-term changes (i.e., beyond the length of a life cycle of a typical product) in consumers' attitudes, lifestyles, and buying patterns.

Respondents in the current study do not frequently take into account technological factors, such as technological advancement in the field or R&D spending (Figure 2.2). Monitoring technological advancements and becoming a technological leader by implementing new technologies can bring competitive advantage (Byun et al., 2018). Both technological leaders and followers need to monitor technological changes on the market and improve their strategy once changes occur (Doha et al., 2018; Aghion et al., 2001).

In the current study, respondents used information about environmental factors to a lesser extent in the PLC (Table 2.2, Figure 2.2). In the short term, this can be a problem with respect to economic factors such as price fluctuations, the current macro-economic situation, and the unemployment level. According to Steenkamp and Maydeu-Olivares (2015), negative macro-economic conditions and unemployment make people become more price sensitive and less quality sensitive, which affects their buying behaviour. Moreover, for products with very long life cycles, there can be an issue due to changes in the ageing of the population if this is not monitored. Ageing affects people's attitudes towards product quality, e.g., older people choose products of higher quality (Steenkamp and Maydeu-Olivares, 2015). Therefore, it is important to investigate and monitor the effect of age distribution on consumers' product acceptance to identify possible quality perception changes over longer times, which could affect product success.

5.2. Consumer data use in different product development phases: opportunities for improvement

In the first two NPD phases (i.e., *opportunity identification* and *product design*), firms frequently use food trend and environmental factor data (Figure 2.3). This can have a positive impact on product success since it allows the discovery of promising product ideas by exploring multiple product ideas and increasing the understanding of consumers' needs (Poretta and Hartmann, 2010). However, the quality of collected consumer data, which can depend on how a particular method was applied, can also have an impact on the quality of ideas and future product success. Unfortunately, the results in Figure 2.3 do not reveal the quality of the data that respondents use. In the *product testing* phase, firms most frequently employ consumer involvement data (Figure 2.3). The number of new ideas drops as product development progresses and the ideas that remain need to become more refined, which could explain the higher need for consumer involvement data and lower use of other data types (Barczak, 2009; Fuller, 2005). On the other hand, it is worrisome that only 54.9% of respondents include consumers directly in the product testing phase to assess consumers' acceptance of new products since this can have a positive impact on product success (Gruner and Homburg, 2000).

In the beginning of the PLC (i.e., *introduction* phase), firms most frequently use environmental factor data (Figure 2.3). This could result from the lack of data on product performance in this phase (e.g., sales data), while at the same time, firms need to invest strongly into promotion and provide attractive prices to compete in the market (Mohammadi and Saghaian, 2017). Using consumer involvement data is also relevant in this phase to compare firm predictions to real data to optimize the PLC management strategies (Urban and Hauser, 1993), but only 31.1% of respondents do so (Figure 2.3). The low utilization of all three data types after the introduction phase of the PLC could imply that the respondents in our study assess the degree of fit between the product and consumers' needs to a lesser extent once products are launched on the market and that they rarely base their PLC management decisions on consumer data. This can have an impact on product success if a change in consumers' needs goes unnoticed (Costa and Jongen, 2006). Unexpected changes in the economic, technological, competitive, and consumer environment can be noticed in a timely manner by systematic monitoring of the environment (Urban and Hauser, 1993). Firms should monitor data during the PLC to discern the forces that move the product from the introduction to the decline phase in the PLC, which can have positive effects on PLC management (e.g., Schmidt and Gary, 2002).

5.3. Possible implications of using different consumer data collection methods for product success

The most frequently used methods to obtain "design for" consumer involvement data by respondents are focus groups, consumer surveys, and the use of the internet and magazines (Figure 2.4). These methods often yield qualitative data on consumers' preferences and needs. Such data are beneficial in the opportunity identification phase to understand consumers' needs and to develop product ideas (Geyer et al., 2018; Creusen et al., 2013; van Trijp and Steenkamp, 2005). However, multiple researchers categorized these methods as passive consumer involvement methods that provide limited guarantees of product success and do not facilitate the development of truly innovative products (Geyer et al., 2018; Janssen and Dankbaar, 2008;

Wind and Mahajan, 1997). By employing only these methods, firms will have less control over their product's success. "Design with" methods, i.e., sensory tests and concept testing, are valuable for product development guidance, improvement, and maintenance (Resurreccion, 2007; van Trijp and Steenkamp, 2005). Moreover, the low use of methods to obtain "design by" data, such as the lead-user method and consumer co-creation (Figure 2.4), suggests that the firms in our study do not frequently involve consumers more actively and deeply throughout product development. Geyer et al. (2018) indicated that the use of the lead-user method in product development projects results in improved product performance forecasts. The use of "design by" methods can be especially useful in developing new to the world products, as such methods uncover latent consumer needs and provide a better understanding of potential causes of product failure (Janssen and Dankbaar, 2008; Kristensson et al., 2008).

Figure 2.5 shows a lack of use of formal methods to obtain data on trends and environmental factors since only competitor analysis could formally be considered as a method. The most frequently used methods (e.g., internet, newsletters, and reports) usually do not provide highly specific data to the food product under development. Respondents in our study most frequently employ low to moderately proactive methods (Figure 2.5), according to the classification by Kahn et al. (2006). More specifically, data on consumer needs are usually collected by passive consumer involvement (e.g., consumer surveys) or through secondary resources (e.g., internet, reports, and food fairs) (Figure 2.5), which is in agreement with other studies (Kristensson et al., 2008; Kahn et al. 2006). A more proactive approach would include "continuous collection and assimilation of suitable information about the consumers' views and needs during product development" (Costa and Jongen, 2006, pg. 461) and could include data collection based on retailers' check-out scanner data, household panels, and attitudinal market research (van Trijp and Steenkamp, 2005). According to Kristensson et al. (2008), for more sustainable success, firms need to use multiple methods for consumer data collection to discover both latent and existing consumer needs.

Our respondents rarely employ modelling methods in product development. Developing simulation computer models (e.g., system dynamics, agent-based) to facilitate product development can be a powerful approach, particularly when resources for testing a product in the real world are limited. By synthesising various types of consumer data in the form of a meaningful computer model, one can yield information about the expected success of a product during its PLC (e.g., Schmidt and Gary, 2002). Statistical methods cannot always support the generation of proper conclusions from data, especially when dealing with complex issues, such as product success among consumers (Sterman, 2004). Complex “white box” modelling methods, such as system dynamics (e.g., Zhao and Zhong, 2015) and agent-based modelling (e.g., Sturley et al., 2017), allow for integration of knowledge and facilitate understanding of the relationships between data and product performance. This can ultimately lead to improved decision-making and to more successful new food products (Sterman, 2004). However, less than 10% of respondents employ these “white box” modelling methods.

5.4. The type of NPD project, firm size, and function have an impact on the type of consumer data used

In our study, respondents engage the least frequently in new to the world types of projects and the most frequently in product improvement, and product line extension projects (Figure 2.6). Likewise, Barczak et al. (2009) reported that in 2003, new to the world projects were the least frequent among various firms, while product improvements and product line extensions were the most frequent projects. There are a few possible reasons for this. New-to-the-world products require 2 to 4 times more resources (Holahan et al. 2014; Ahmad et al., 2013; Barczak et al., 2009; Janssen and Dankbaar, 2008) and the food industry is an industry with relatively small R&D expenditures (Costa et al., 2016; Costa and Jongen, 2006). Moreover, Barczak et al. (2009) explained that new to the world products require longer development times than incremental innovations. Interestingly, we found a relationship between undertaking new to the world projects and the use of “design by” data (Table 2.3). Similarly, Janssen and Dankbaar (2008) reported that food firms developing truly new products more often employ “design by” consumer involvement data. New to the world products usually have a higher chance of success (Barczak et al., 2009). Costa and Jongen (2006) reported that truly new products fail 24% less often than incremental innovations. In the future, firms that participated in our study could consider using “design by” data more frequently and invest in the development of new to the world products to increase chances of success.

Moreover, a significant relationship between firm size and the use of consumer involvement data has been observed (Table 2.4). Apparently, small firms less frequently use consumer involvement data or involve consumers in the product testing phase, whereas large firms more often use “design for” and “design with” data and undertake consumer surveys, concept testing, and sensory tests. Steffen (2018) suggested that small firms commonly base their strategy on intuition, which can have a negative impact on their product success. Limited use of sensory tests and concept testing may lead to lower product success, as this suggests that R&D professionals assume they know best what consumers want (Wind and Mahajan, 1997). Firms often do not include consumers to an appropriate extent due to limited resources (Dijksterhuis, 2016). In situations with limited resources, firms must wisely choose methods to generate consumer data (Sumberg, 2013). For example, conjoint analysis does not require intensive consumer involvement but provides data that can be used to assure a high likelihood of product success (Green et al., 2001; Wind and Mahajan, 1997).

Lastly, statistical analysis data suggest that the respondents' function relates to the use of consumer data. We observed a relationship between belonging to the marketing function and using environmental factor data in the introduction phase of the PLC (Table 2.5). This could be explained by the nature of the activities in this phase, which are oriented at promotion of the product. Here, environmental factors could be used to understand changes among consumers to adjust promotion strategies (Mohammadi and Saghaian, 2017; Urban and Hauser, 1993).

5.5. Study limitations and recommendations for further research

Although the authors aimed at approaching diverse firms at the Anuga Food Fair and on LinkedIn (in terms of country, size, and product category), due to differences in firms' visibility and approachability, there is the possibility of biased selection. Some bias could originate from contacting respondents from the authors' personal network, which is particularly visible by the Netherlands being the most represented country in the study. Moreover, respondents mainly belonged to large companies (61.1%), followed by medium (22.1%) and small firms (16.8%). Future research could focus more deeply on data use in medium and small firms. In the current conceptual framework, we initially considered the three data types independently, but there are likely interactions between them. Therefore, future research could examine the interconnections between the three consumer data types and the consequences for their use in product development of specific product categories.

6. Conclusions and implications for practitioners

The professionals in our study extensively use all three data types in NPD (consumer involvement, food trends, and environmental factors), while their use is significantly lower in the PLC. They use all three types of consumer data most frequently in the opportunity identification and product design phases of NPD. Only employment of consumer involvement data remains high in the product testing phase, which indicates respondents' awareness of the importance of consumer data for successful NPD. However, significantly lower use of all three data types in the PLC, especially after the introduction phase, indicates that the respondents in our study assess the degree of fit between a product and consumers' needs to a lesser extent once products are launched on the market. This can have an impact on product success if a change in the degree of fit goes unnoticed. Moreover, respondents frequently use methods such as focus group, consumer surveys, and the internet and magazines. "Design by" methods, such as co-creation and lead user methods, are rarely used and their use is associated with participating in new to the world projects. Interestingly, most of the respondents do not work on new to the world projects and they mainly work on projects such as product improvements, product line extensions, and new product lines. Finally, there is an association between firm size and the type of data and methods employed in NPD. Respondents from small firms use consumer involvement data in NPD significantly less often, particularly in the testing phase, and they less often employ sensory tests, compared to respondents from large companies. Moreover, respondents from large companies use consultancy and marketing agencies to obtain trends and environmental factor data significantly more often than respondents from small firms.

Professionals in food product development could improve the chances of product success by strategically tailoring their data collection to the type of product innovation they are undertaking and to the phase of product development. Moreover, they could employ a higher level of consumer involvement in product development, i.e., by using "design by" methods, and by using multiple methods to discover both latent and existing consumer needs, especially if they want to deliver new to the world products. Furthermore, they could dedicate attention to establishing formal methods for collecting data on food trends and environmental factors. Currently, these types of data are the most frequently collected through secondary sources (e.g., newsletters, reports, food fairs, and the internet).

Lastly, to integrate various data and to improve understanding of the connection between collected consumer data and product performance, European firms could move towards the use of complex computer modelling and simulation, such as system dynamics or agent-based modelling. The scientific community could aid that effort by exploring the potential of the use of such modelling methods in managing food product development.

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Chapter 3

A systems approach to dynamic performance assessment in new food product development

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Abstract

Despite a great deal of research and knowledge, the failure rate of new food products is still high. Developing new food products is complex, since multiple functions, i.e., marketing, technology, and consumer researchers, are involved. How their decisions interrelate and affect product performance over time, i.e., throughout product life-cycle, has been scarcely studied for the food domain. Systematic assessment of product performance factors can lead to improvement, but such approach is yet lacking for new food products. The study aimed at understanding which factors are relevant to assess performance of new food products during their life-cycle. An integrated framework for performance assessment of a new food product was developed by performing a structured literature review and by using systems approach principles to synthesize the review findings. The integrated framework represents the three main functions in new food product development – consumer research, technology and marketing, and consists of 46 variables relevant for managing food performance during its life cycle. Seven reinforcing and four balancing feedback loops were identified, which provide insight in the causal relations between variables. The integrated framework provides understanding of how each of the functions contributes to the food product's overall performance and how they can anticipate consequences of numerous changes throughout product's life on the overall product's success, e.g., sales. This system representation helps decision-makers to get insight into behaviour of the whole system and to leverage the performance of new food products.

1. Introduction

Successful new products have been recognized as critical for business performance of manufacturing companies in today's fast changing and competitive markets (Kalluri and Kodali, 2014; Barczak and Kahn, 2012). Consequently, designing appropriate strategies for new product development (NPD) has attracted a lot of attention. Researchers have been trying to uncover the drivers of successful new product performance (Kalluri and Kodali, 2014) and have emphasized the importance of measuring performance (Alegre et al., 2006; Montoya-Weiss and Calantone, 1994) to assure viable product life-cycle. Nevertheless, it has been reported that 50 – 75% of consumer-packaged goods (CPG) do not achieve desired success level (Dijksterhuis, 2016).

Also, the food manufacturing industry has been recognized as a CPG industry with high new product failure levels (Ryynänen and Hakatie, 2014; Earle et al., 2001). However, there is a literature gap in new food product development research (Ryynänen and Hakatie, 2014; Mattsson and Helmersson, 2007). A recent review by Kalluri and Kodali (2014) revealed that from the 1127 reviewed articles, only 2.8% focused on NPD in the food industry in the period from 1998 to 2009. Only four articles aimed at researching NPD performance measures and drivers, with two having a financial and market-based focus, one was researching technical measures and drivers, and one was assessing general performance drivers.

Historically, we can distinguish three main research perspectives in new food product development. The first one is the technological perspective, where technological progress (e.g., the discovery of freezing, pasteurization, etc.) was the main driver of early research and innovation. The second perspective is the market-oriented approach, which was initiated by establishment of the marketing field, appearance of supermarkets, new packaging, and increased competition in the mid-60s (Goldenberg and Shapira, 2009; Wolf, 2009; Earle, 1997). More recently, consumer-led product development gained attention to further improve product success (van Boekel and Linnemann, 2007; Earle, 1997). Factors of technological and consumer product performance have traditionally been determined by food and consumer scientists, while market-oriented approach has been part of the marketing and management field. However, the need for integration of marketing, consumer research, and food technology to improve new food product performance has been recognized and discussed in the existing literature (e.g., Straus, 2009; Earle, 1997).

A few researches attempted to establish an integrated approach in the field of food product development. For example, Moskowitz et al. (2009), based on their experience, integrated NPD goals of various functions into 5 elements of the new food product success equation. However, a systematic approach that considers crucial cross-functional activities in NPD (i.e., of technology, marketing and consumer research functions) (McCarthy et al., 2006), is missing. Moreover, the dynamic nature of factors influencing performance has largely been overlooked (Rodrigues et al., 2006; Ford and Sterman, 1998). NPD and product life-cycle (PLC) activities may continue for years and initially measured values of factors may change over time, which is why their dynamic nature needs to be considered. In other words, changes in factors need to be anticipated and measured multiple times throughout product's life. In order to study the complex cross-functional and dynamic nature of food product performance, we use a systems approach in this paper. This approach aims at analysing each component of a system and the interactions between those components, which are finally synthesized in a comprehensive system representation (Dettmer, 2006).

The aim of the study is to develop an integrated framework for dynamic assessment of new product performance. Based on a structured literature review, we identified major variables in the NPD system, including the marketing, technology, and consumer function, which can affect new product performance. This was followed by development of means-criteria system diagrams for each function, which show interconnections between variables and new product performance. Finally, these diagrams were synthesised into the integrated framework.

2. Systems approach to new product development

2.1. Systems approach concept

Systems approach to problem solving is based on identifying and understanding variables in a complex system and their interconnections predicting dynamic system behaviour and modifying it to achieve desired performance (Arnold and Wade, 2015). Moreover, in systems thinking there is a shift in relevance from linear to cyclical structure, as the interconnected variables may form feedback loops, which means that they form a closed sequence starting and ending with the same variable (Richardson and Pugh III, 1981). Reinforcing feedback loops represent a succession of cause-effect relations that amplify change in the initial variable. Balancing feedback loops counteract an initial change. These feedback loops are the main generator of dynamic system behaviour and their identification is crucial for illustrating performance of dynamic complex systems (Kunc, 2012; Barlas, 2009; Sterman, 2004).

System dynamics (SD) is a formalised systems approach. It includes assessing problems from a dynamic perspective, i.e., taking changes over time into account (Barlas, 2009), and usually follows a qualitative and quantitative phase. The output of the qualitative phase is a causal map, which describes system variables and their interconnections in terms of cause-effect relationships and feedback loops (Arnold and Wade, 2015; Sterman, 2004; Richardson and Pugh III, 1981). Causal maps form the basis for the quantitative phase, in which a computer-simulated model is developed. Although the causal maps can be generic, the quantitative models are mostly developed for a specific case and require quantitative data to generate simulation models. The current study focused on the qualitative phase.

2.2. Problem articulation for dynamic assessment of new food product performance

The first step comprises of defining key concepts and system boundary (Sterman, 2004). The focus of the current study is on performance of a food product during its product life-cycle (Figure 3.1), where the product need to be monitored, as unexpected events and new challenges can occur (Urban and Hauser, 1993). As key concepts, we distinguish the three main functions in NPD that produce and use information to optimize food product performance – i.e., marketing experts, food technologists, and consumer researchers (van Trijp and Steenkamp, 2005; Earle et al., 2001). Main activities of the *consumer research function* include identifying consumer opportunities and weighting product's attributes against consumers' needs (van Boekel and Linnemann, 2007). It also includes information related to sensory research (Grunert, 2015). The *marketing function* selects which opportunities to exploit, analyses markets, tailors advertising, and weights products against firm's values and benefits. The *food technology function* realizes technological product characteristics and includes R&D, engineering, and production experts (Luning and Marcelis, 2007; van Trijp and Steenkamp, 2005; Earle et al., 2001). These three functions should have a continuing interaction during product's development and product life-cycle (Earle et al., 2001).

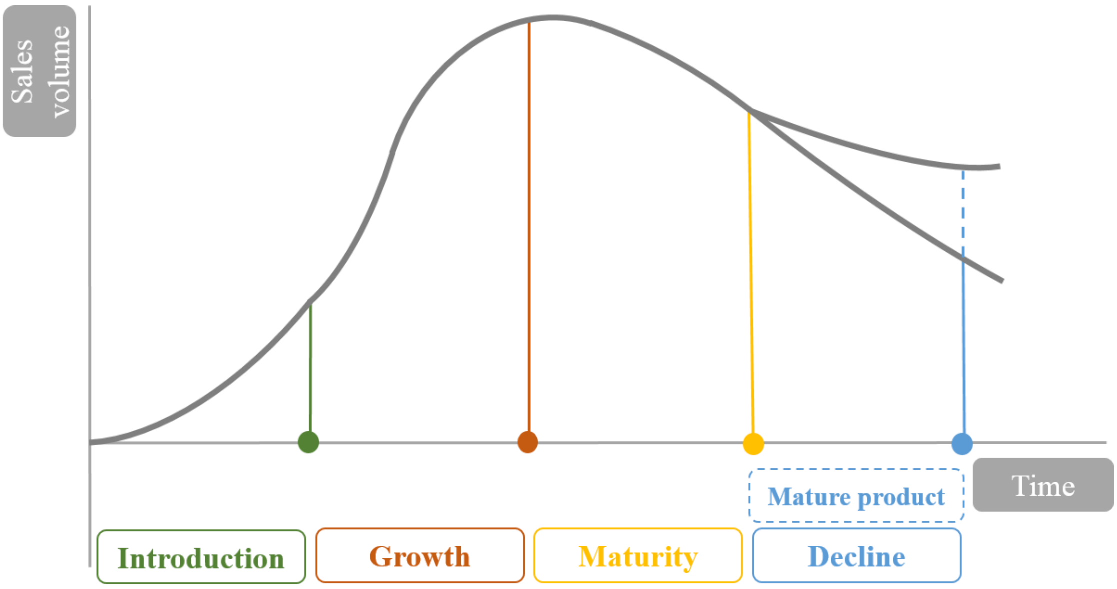

Figure 3.1. *Typical behaviour of product's performance in product life-cycle phases (introduction, growth, maturity, decline), expressed as sales volume over time (adapted from Weinstein (2002)).*

2.3. System conceptualisation by developing means-criteria system diagrams

The next step, system conceptualization, includes mapping the variables and feedback loops, which represent hypotheses about the sources of dynamic behaviour (Sterman, 2004). Although a common tool for model conceptualization in system dynamics are causal loop diagrams, it is not uncommon to choose another diagramming form if it is more appropriate (e.g., Olaya and Gomez-Quintero, 2016; Pruyt, 2013). Causal loop diagrams are unable to represent the decision-making process explicitly (Olaya and Gomez-Quintero, 2016), which can lead to less precision in linking system variables and less appropriateness of representing an organization (Morecroft, 1982). Here, we combined elements of system analysis and system dynamics to develop a dynamic causal map of a system in the form of means-criteria system diagrams by identifying feedback loops in system diagrams (Enserink et al., 2010).

To understand the possible causes of NPD failure, insight in lagging and leading performance variables and their causal relations is needed (Wang and Chuang, 2016). Lagging performance variables are outcome performance measures and leading performance variables are drivers of performance (Barnabè, 2011). Causal relations between lagging and leading performance variables can be presented in the form of means-criteria system diagrams (Enserink et al., 2010).

In Figure 3.2, *means* represent actions with which each function influences the system to achieve desired goals (Morecroft, 2010). Means are the points where NPD functions can influence the existing feedback loops. *Criteria* (lagging performance indicators) are measured to assess if desired goals are achieved. The cause-effect relationship between means and criteria is explained with *internal variables*, representing leading performance indicators. According to Enserink et al. (2010), *external factors* are all the variables that affect the system, but cannot be influenced by means or internal variables. However, as external variables we also considered some variables that are influenced by internal variables, but that cannot be influenced by means of one of the three corresponding functions.

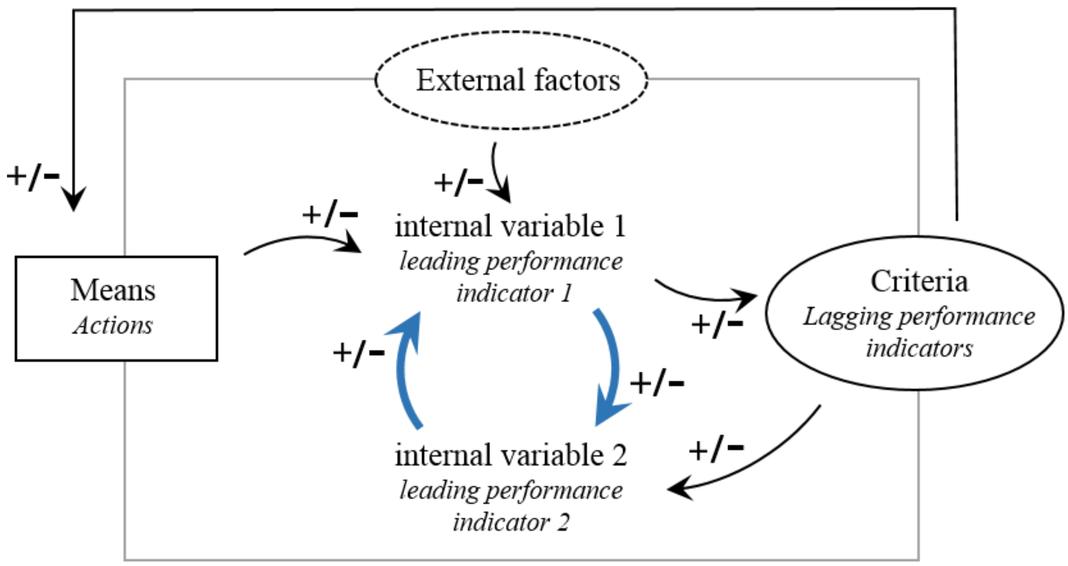

Figure 3.2. *Example of a means-criteria system diagram with main elements: means, criteria, internal variables, and external factors (adapted from Enserink et al., 2010). Arrows represent cause-effect interactions between variables. Each arrow has one polarity sign (+ or -). Plus sign (+) means: all else equal, if variable 1 increases (decreases), then variable 2 increases (decreases). Minus sign (-) means: all else equal, if variable 1 increases (decreases), then variable 2 decreases (increases). Blue arrows represent a feedback loop.*

3. Structured literature review to identify variables

To identify relevant variables and to build means-criteria system diagrams, a *configurative literature review* was performed according to the guidelines set by Gough et al. (2012a; 2012b).

Purposive search and *reference list checking* was performed to collect relevant literature (Gough et al., 2012a). The review (period 1998-2009) by Kalluri and Kodali (2014) served as the basis to identify the first body of literature and was combined with a second literature search on Scopus database, gathering relevant review papers from the year 2010 to 2016. Terms “product development”, “new product”, and “product innovation”, as by Kalluri and Kodali (2014), were used (see Supplementary material 2 for details of the literature search). Inclusion criteria were: papers from NPD commercialization and NPD performance measures research streams (Kalluri and Kodali, 2014), publications addressing NPD from consumer non-durables perspective (or mixed, where consumer non-durables were analysed together with durables), with project and/or product level of analysis. Special attention was given to papers on marketing, consumer research, and technology in food NPD. Only papers starting from the year 1990 were included.

Figure 3.3 shows the data analysis, which included *line-by-line coding* without pre-existing themes and categorizing of data (Gough et al., 2012a). In phase 1, relevant text from each included study was copy/pasted into a separate document. The relevant text included sentences naming and defining variables, descriptions of causal relations between variables and polarity of causal relation. By variables we here refer to indicators, determinants, antecedents or factors of NPD performance, and performance measures in the analysed literature. Phases 2-4 of data analysis included categorization and cleaning of extracted text.

Iterative data synthesis was done in a ‘line of argument manner’ (Gough et al., 2012a). Causal relationships between the function specific variables from phase 4 were identified according to Vennix (1996), in iteration with coding of variables with similar meaning. Means-criteria analysis was performed separately for each function. The obtained causal links between coded variables served as a basis for defining the means, external factors, and all other internal variables, while performance measures were used to define criteria.

4. Means-criteria system diagrams to dynamically assess new food product performance

Figure 3.4 shows the means, criteria, internal variables, and external factors of the marketing [A], technology [B], and consumer research [C] functions, which can affect new product performance.

	Data analysis				Data synthesis
	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
Action	Reading the full text of selected papers	Analysing the lines of text from phase 1	Categorizing the variables from the phase 2 into separate tables	Removing duplicates in tables from phase 3	Iterating between causal mapping and coding
Result	Lines of text with variables and belonging sentences from relevant papers, categorized by publication	Table consisting of numbered variables, their sources and accompanying sentences	One table consisting of performance measures; three tables consisting of the rest of the variables, one for each function	Lean tables ready for phase 5: one table for performance measures categorised by the function, three tables for other variables (each belonging to one function)	Three means-criteria causal diagrams, one for each function; final versions of all tables with coded variables

Figure 3.3. *Process of data analysis and synthesis; phases 1-4 are linear and phase 5 is iterative.*

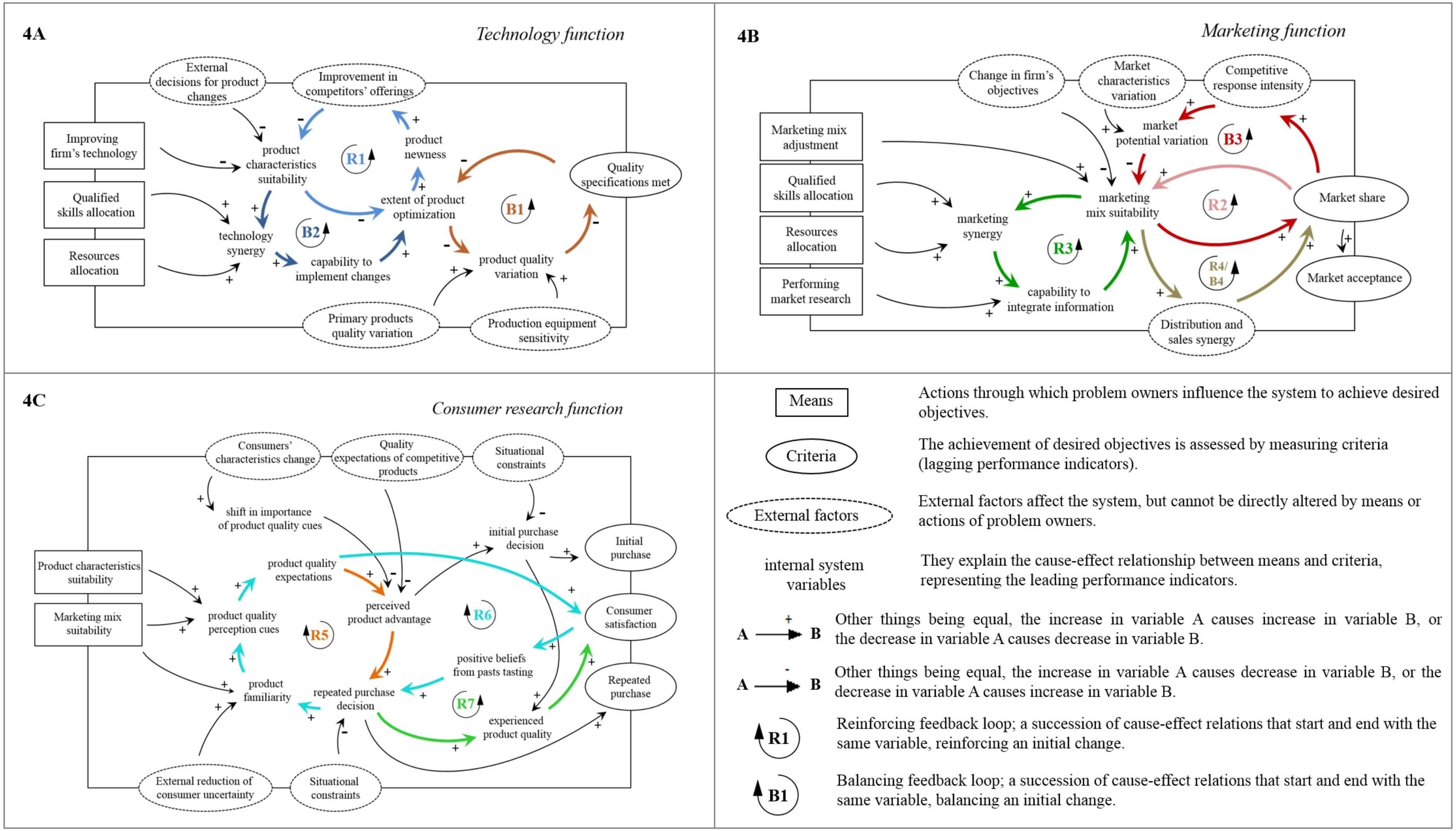

Figure 3.4. *Means-criteria system diagrams of the [A] technology function; [B] marketing function, and [C] consumer research function variables. All feedback loops are specified in Table 3.1. Definitions of variables are in Appendix 1 in the end of this chapter.*

Table 3.1. *List of feedback loops from Figure 3.4*

	Name	Mechanism
BALANCING FEEDBACK LOOPS		
B1	product quality variation	Product quality variation affects meeting quality specifications. This, in turn, requires a certain extent of product optimization to adjust product quality.
B2	technology function capability	Variation in technology synergy can affect technology function’s capability to implement changes, for example, in a situation where there is an adjustment in product characteristics suitability due to improvement in competitor’s offerings. This may have an effect on the extent of product optimization and, ultimately, on product newness.
B3	competitive response intensity	Changes in market share, due to the adjustment of marketing mix suitability, may lead to changes in competitive response intensity and market potential variation. Consecutively, this may require even more changes in marketing mix suitability.
B4	distribution and sales affect competitive response	Changes in distribution and sales synergy may lead to a difference in market share, which may results with changes in competitive response intensity. Similarly to loop B3, this may require even more change in distribution and sales synergy.
REINFORCING FEEDBACK LOOPS		
R1	product characteristics newness	Improvements in competitors’ offerings may lead to less product characteristics suitability on the market. This may require a certain extent of product optimization to adjust product newness, which may result with even more improvement in competitors’ offerings over a longer period.
R2	marketing mix suitability	Change in market share may be an implication of a need to adjust marketing mix suitability to advance market share in the future.
R3	marketing function capability	Change in marketing synergy may affect marketing function’s capability to integrate information and to adjust marketing mix suitability.
R4	distribution and sales affect market share	Change in market share may be an implication of a need to adjust marketing mix suitability, which may affect distribution and sales synergy and may lead to even more changes in market share in the future.
R5	product familiarity	Product familiarity affects consumers’ product quality perception cues and product quality expectations, which consequently affects consumers’ perceived product advantage. Changes in perceived product advantage may lead to variation in repeated purchase decisions and product familiarity (on an aggregated level).
R6	quality expectations affect satisfaction	Changes in consumers’ product quality expectations lead to differences in consumer satisfaction, positive beliefs from past tasting, repeated purchase decisions, and even more changes in product quality expectations (on an aggregated level).
R7	experienced quality affects satisfaction	Changes in experienced product quality lead to difference in consumer satisfaction, positive beliefs from past tasting, repeated purchase decisions, and even more changes in experienced product quality (on an aggregated level).

4.1. Means-criteria system diagram of the technology function

Figure 3.4A shows the 14 identified technology function variables. The three technology means include *improving firm's technology* (e.g., changing manufacturing equipment, manufacturing process or ingredients), *resources allocation* (e.g., hiring more people) and *qualified skills allocation* (e.g., hiring people with special skills, investing in training) (Pattikawa et al. 2006; Di Benedetto, 1999; Kaul and Rao, 1995). They represent the main actions that affect the main criteria of the technology function *quality specifications met* (Langerak et al. 2004; Griffin and Page, 1996; Kaul and Rao, 1995). The external factors are: *external decisions for product changes*, *improvement in competitors' offerings*, *primary products quality variation*, and *production equipment sensitivity* (Calantone et al., 2006; Zhang and Doll, 2001; Kristensen et al., 1998; Kleinschmidt and Cooper, 1991)

Moreover, figure 3.4A shows three feedback loops. The balancing feedback loop B1 assures that the product meets quality specifications (Li et al., 2015). Decrease in meeting quality specifications, e.g., due to variation of primary product quality and production equipment sensitivity (Kristensen et al., 1998), would lead to an increase in *product quality variation*. This would require an increase in *extent of product optimization*, to increase product's chances of meeting quality specifications (Li et al., 2015).

The reinforcing feedback loop R1 shows the influence of increased *product newness* on the future *product characteristics suitability* on the market (and subsequently for further product newness*)*. Improving the firm's technology (e.g., by investing in it or by developing it in-house), or any other external product changes (e.g., change of suppliers, changes demanded by marketing function), may initially affect the suitability of product characteristics (Kaul and Rao, 1995). After the product has been optimized for an existing market, the result can be increased product newness. Nevertheless, increased product newness may trigger improvement in competitors' offerings, which may lead to less *product characteristics suitability* for the existing market situation in the future (Kock et al., 2011). Improving product's newness is advantageous for a certain period of time, but it is necessary to be aware that increased product newness may produce a response from the competitors on the market (Kock et al, 2011). On the other hand, monitoring *improvement in competitors' offerings* can lead to timely product improvement to extend the product's life cycle (Calantone et al., 2006).

The continuous increase in product newness is limited by balancing loop B2, which defines firm's capability to implement changes. More specifically, it shows that a decrease in product characteristics suitability can lower *technology synergy,* which represents the fit between company's resources (e.g., labour force, capital), skills (e.g., knowledge), and project needs (Ngamkroeckjoti and Speece, 2008; Montoya-Weiss and Calantone, 1994). Decreased technology synergy may negatively affect the capability to optimize a product's characteristics (Di Benedetto, 1999), due to inadequate resources or skills.

4.2. Means-criteria system diagram of the marketing function

The means-criteria system diagram for the marketing function (Figure 3.4B) consists of 14 variables. The main criteria are *market acceptance,* describing the state in which the product satisfies a sufficient number of consumers for a firm to continue its production (Aryana and Boks, 2012), and *market share,* showing the sales volume of a product in a market (Cooper and Kleinschmidt, 1995). Market share can be affected by the variable *marketing mix suitability*, which includes suitability of price, product attributes, and market communications for a certain product on a market (Hultink et al., 1998; Kaul and Rao, 1995). The suitability of marketing mix may be disrupted when there is a *change in firm's objectives*, *market potential variation*, or decrease in market share, or simply when the marketing function decides to perform actions towards *marketing mix adjustment* due to any other internal reasons. Changes in a firm's objectives can include strategic corporate objectives, such as changes in firm mission or allocation of resources to other products to prevent product cannibalization (Krishnan and Ulrich, 2001; Di Benedetto, 1999; Hultink et al., 1998). The variation in market potential is determined by *market characteristics variation* (e.g., needs of consumers, trends variation, market size) and *competitive response intensity*, i.e., the level of competition's response to a new product introduction (Tsai et al., 2013; Evanschitzky et al., 2012; Henard and Szymanski, 2001).

Figure 3.4B shows three reinforcing (R2, R3, and R4) and two balancing (B3 and B4) loops. The reinforcing loop R2 shows, for example, that as marketing mix suitability increases, market share may increase as well. Although an increase in market share may be an indication of high marketing mix suitability, high market share may indirectly decrease that variable through the loop B3. The balancing loop B3 demonstrates that rise in market share may lead to increased competitive response intensity, which can be an earlier implication of the lowered marketing mix suitability than lowered market share (Tsai et al., 2013; Di Benedetto, 1999; Kleinschmidt and Cooper, 1991). To maintain high future market share, marketing mix adjustment may be needed already when the competition introduces product changes (Åstebro and Michela, 2005) and not only when the firm notices decreased market share. As marketing mix suitability decreases, there may be a decrease in *marketing synergy*. Marketing synergy represents the fit between necessary resources, skills, and project needs (Tsai et al., 2013; Pattikawa et al., 2006; Cooper and Kleinschmidt, 1995). Moreover, if market research is not timely performed to observe changes in the market, *capability to integrate information* into a product is lowered (since relevant information is not available to managers), which may also result in lowered marketing mix suitability. Therefore, firms need to continuously perform market research and maintain adequate skills and resources to assure high marketing synergy and capability to integrate information (Tsai et al., 2013, Langerak et al., 2004, Hart et al., 1999). *Qualified skills allocation* (e.g., available knowledge) and *resources allocation* (e.g., firm's labour force and capital) are two means that managers can invest in to improve marketing synergy (Krishnan and Ulrich, 2001; Montoya-Weiss and Calantone, 1994). Low marketing synergy can be an early sign of future product performance problems (Tsai et al., 2013).

Lastly, reinforcing loop R4 shows that *distribution and sales synergy* is an important factor in achieving desired market share. Firm's ability to utilize existing distribution channels and sales personnel is important for establishing good relations with retailers and facilitates communication of product benefits to end consumers (Calantone et al., 2006). This, in turn, is balanced by competitive response intensity, since the distribution and sales synergy variable is part of the balancing loop B4.

4.3. Means-criteria system diagram of the consumer research function

Figure 3.4C depicts 19 variables of the consumer research function. It reveals the consumers' decision-making process, preceding the *initial* and *repeated purchase decision* (Li et al., 2015; Griffin and Page, 1993). Consumers' decision-making starts with the formation of *product quality perception cues* by observing the food product before purchase (Grunert et al., 2011). Consumers' perception cues are based on product's attributes (Li et al., 2015; Lange et al., 2000). Product attributes are determined by levels of product characteristics, or physical product features, and marketing mix elements (e.g., external product information, sensory, health and convenience attributes, and price) (Luning and Marcelis, 2009; Kaul and Rao, 1995). Therefore, any changes affecting *product characteristics suitability* or *marketing mix suitability* may affect product quality perception. From perceived product quality cues, *product quality* *expectations* are formed (Grunert et al., 2011). Moreover, prior to purchase, product is weighted against competing products on the market. Consumers compare competing products on the market to form *perceived product advantage*, which is influenced by *the importance of product quality cues* and *quality expectations of competitive products* (Calantone et al., 2006; Kaul and Rao, 1995). Importance of product quality cues arises from consumers' socio-economic, psychological, and cultural characteristics (Carlucci et al., 2015). Any change in these characteristics may cause a *shift in importance of product quality cues* (Aryana and Boks, 2012). For example, becoming more concerned about the environment can cause a shift in relative importance from the product's price to its sustainability and can affect utility derived from each product. Initial purchase occurs if consumers perceive a product has an advantage to competing products (Grunert et al., 2011; Tsai et al., 2013).

Repeated purchase occurs if consumers' product quality expectations are confirmed by *experienced product quality* at the moment of consumption (Mueller et al., 2010). Discrepancy between product quality expectations and experienced product quality is usually measured with *consumer satisfaction* performance measure (Grunert et al., 2011; Hultink et al., 1998; Nancarrow et al., 1998). However, the next purchase does not necessarily happen immediately after the initial purchase. Consequently, consumers use their memories of satisfaction, or *positive beliefs from past tasting*, to make repeated purchase decision (Mueller et al., 2010). Here, with the variable perceived product advantage, the product is once again weighted against competing products before making repeated purchase decision.

Consumers' decision-making process is also influenced by external factors. While the *external reduction of consumer uncertainty*, such as word-of-mouth (Kotler, 2011), has a positive effect on purchase by increasing *product familiarity*, most of the other external factors have negative effects. *Consumers' characteristics change* can lead to less compatibility of the product with consumers' habits and less derived product utility (Carlucci et al., 2011). Consequently, if consumers derive more utility from competing similar products, there is less perceived product advantage and less initial and repeat purchase (Tsai et al., 2013; Langerak et al., 2004; Cooper and Kleinschmidt, 1995). *Situational constraints*, such as availability, time, and money constraints, also have a negative effect (Carlucci et al., 2015; Kaul and Rao, 1995).

The two means of the consumer research function are product characteristics suitability, and marketing mix suitability (e.g., price improvement, marketing communications such as advertising and promotion, brand strengthening). Consumer researchers can assess the influence of changes in these variables on consumers' decisions and their buying behaviour by performing consumer testing. However, in practice usually these variables are influenced by the marketing function, by adjusting marketing mix in general, and product attributes in particular, or partially by technology function by adjusting product characteristics, which can also affect product attributes (Kaul and Rao, 1995).

Figure 3.4C shows three feedback loops affecting performance from the consumer research perspective. The R5 reinforcing feedback loop implies that repeated purchase increases with improved product quality perception cues (Li et al., 2015), by raising product familiarity (Calantone et al., 2006), which leads to even more repeated purchase decisions. This is further reinforced by the loops R6 and R7. The loop R6 demonstrates that higher experienced consumer satisfaction leads to more positive beliefs from past tasting (Carlucci et al., 2015) and more repeated purchase decision. The loop R7 shows that higher experienced product quality leads to more consumer satisfaction and more repeated purchase decisions (Mueller et al., 2010).

5. Integrated new food product performance framework

Figure 3.5 presents the integrated framework for dynamics assessment of performance of a new product. The integrated framework explicitly shows how the three functions are interconnected and how they mutually contribute to the overall performance criterion, which is *product sales*. Figure 3.5 shows that the marketing function is connected with the other two functions through the variable *marketing mix suitability*. Lowered marketing mix suitability may trigger marketing function to propose *external decisions for product changes*, some of which could require adjustment of *product characteristics suitability* by the technology function (Kaul and Rao, 1995). Additionally, modifying product characteristics suitability (e.g., by *improving firm's technology*) by technology function might call for necessary changes in marketing mix suitability. Any changes in marketing mix suitability can directly influence the consumer research function (Hultink et al., 1998). If marketing mix elements change (e.g., promotion, new packaging design, price), consumer research function should assess how the new marketing mix elements affects consumers' *product quality expectations* and, ultimately, *consumer satisfaction*. If the new consumer satisfaction is not as high as expected, this would have implications for the marketing function to further improve marketing mix suitability and the cycle would start again.

Consumer research function and technology function are also connected with *consumer satisfaction* variable (Figure 3.5). For example, consumer (un)satisfaction, resulting from *experienced product quality* (e.g., if taste of the product is not satisfactory, especially if there have been some changes in formulations or production process), might be a sign of product quality variation, which has implications for the technology function to optimize product characteristics. To finish the cycle, once the technology function optimizes product characteristics (i.e., *extent of product optimization* variable) and the product's *quality specifications* are *met*, consumer research functions needs to assess if consumers can detect any product quality variation that might affect consumer satisfaction. Technology function needs to detect product variation in time and strive to meet quality specifications, as any variation that went unnoticed may affect consumer satisfaction and may lead to fewer repeated purchase. Product quality variation may occur, for example, due to the variation in quality of raw materials.

Finally, all three functions influence product sales – as the main criterion of product performance on the firm level. At the same time, product sales may also influence the means and actions the firm undertakes to adjust performance. For example, low profits due to low product sales may cause less resources allocation to the three functions and less investment in improving firm's technology and *skills* of current staff (e.g., less training), decrease the extent of *market research* performed, or cause a decrease in *resources* (e.g., by hiring less employees, or using cheaper materials for production).

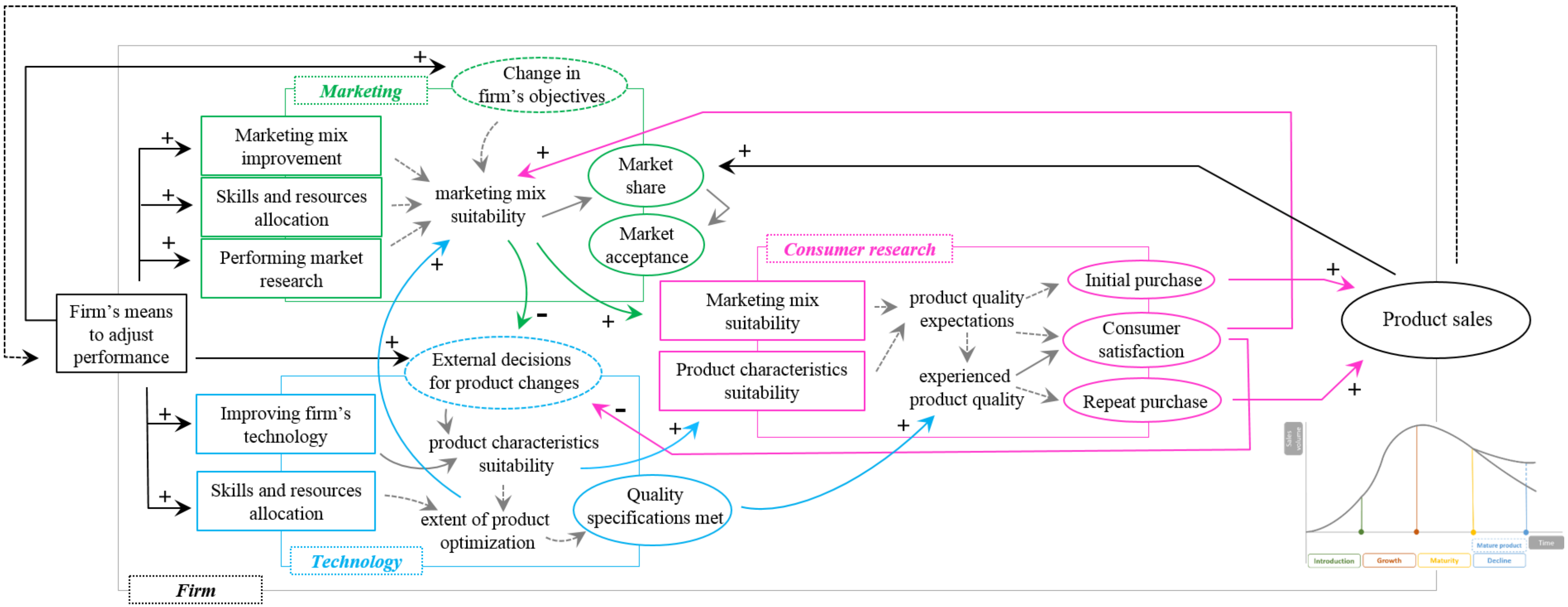

Figure 3.5. *Integrated framework for dynamic assessment of performance of a new food product. Dashed grey arrows imply that some variables and polarity (+ or -) of arrows inside each function from Figure 3.4 have been omitted to avoid cluttering.*

6. Usefulness of the means-criteria system diagrams and the integrated framework

The integrated framework in Figure 3.5 and the three means-criteria system diagrams in Figure 3.4 provided a basis for displaying the dynamic, interconnected nature of NPD and the PLC performance in food industry. Figures 3.4 and 3.5 move away from the traditional linear process view of NPD and PLC. Although having a well-established NPD process is relevant for success, it does not fully provide understanding of mechanisms through which certain activities in NPD and the PLC affect performance of a product. Eleven identified feedback loops (see Figure 3.4 and Table 3.1) depict the cyclical mechanisms from which performance of a product arises over time and which need to be considered in today's fast changing markets to achieve success.

Most people are not able to deal with dynamic complex issues adequately without the help of models (Pruyt, 2015). The integrated framework should facilitate comprehension of the consequences of practitioners' activities on product performance at any phase of NPD or the PLC, as system models can facilitate understanding the links between decisions and performance (Torres et al., 2017). By following the framework, product related changes, changes in the firm's strategy or changes in environment (e.g., in competition, consumers' characteristics) can be appropriately and timely managed and communicated between the functions to assure satisfactory performance. For example, any planned improvement in firm's technology might be an opportunity for marketing to alter marketing mix and to improve product attributes to increase consumer satisfaction. On the other hand, any decrease in skills and resources of marketing or technology function can be an early sign of possible challenges in optimizing products to meet quality specifications or improving marketing mix suitability. Furthermore, marketing research performed by marketing function should be shared frequently with other functions, as it might not only have implications for marketing mix suitability, but can also be an opportunity to change product characteristics, improve consumers' experienced product quality, and increase consumer satisfaction. Moreover, the framework stresses the importance of periodical assessment of consumer satisfaction by consumer researchers. Consumer satisfaction can change due to various reasons. Knowing that the sales are lower is not a sufficient indication of which marketing mix or product characteristics elements need improvement. Apart from using the framework for improving ongoing projects or products, practitioners can use it to analyse past products to learn about possible causes of past failures or successes. Since Figures 3.4 and 3.5 represent the product performance on two different levels, function and firm, respectively, practitioners can choose the level of detail of analysis. While Figure 3.5 offers a broader overview of how each function affects performance, Figure 3.4 gives more detail about function specific mechanisms that are responsible for failure or success of a product. To minimize bias when using means-criteria system diagrams and the integrated framework practitioners can utilize definitions and references for each variable provided in Appendix 1, together with the information in Table 3.1, which provides clarification of feedback loops in means-criteria system diagrams.

The integrated framework and means-criteria system diagrams are qualitative and scientists can use them as an opportunity to explore the ways of quantifying multiple variables, especially the ones which are part of feedback loops. This could reinforce future development and broader use of computer models and simulations to study complex dynamic issues in agri-food systems (Perrot et al., 2016; Perrot et al., 2011). For example, variables of the consumer research function, such as positive beliefs from past tasting, product familiarity, or perceived product advantage, substantially influence purchase decisions. However, they are not frequently part of consumer studies. Such variables, if quantified, could find their use in food product management. Variables such as competitive response intensity, quality expectations of competitive products, and improvements in competitors' offerings showcase the importance of studying consumers' food product satisfaction as part of a broader environment that includes competition, instead of performing isolated product consumer and sensory research. Moreover, the framework revealed variables such as marketing synergy, technology synergy, and capability to implement changes and integrate information. These concepts, which are frequently mentioned in management literature as very important for product performance, have not yet been comprehensively defined in the food domain.

The integrated framework in Figure 3.4 and the three means-criteria system diagrams in Figure 3.5 represent an idealised dynamic food product performance assessment. Future framework validation could indicate which causal links and mechanisms are the most relevant in practice in food firms. Individual interviews with food industry product development professional could be performed to compare their decision-making process and the integrated framework. Furthermore, group model building workshops with whole product development teams could be performed (e.g., Vennix, 1996). Group model building aims at solving dynamic problems, such as food product sales and developed diagrams can be converted into system dynamics computer models. Although these models are used to design optimal strategies, here they can also be useful for comparison with the integrated framework and means-criteria system diagrams.

7. Conclusions and further research

The literature review revealed 46 variables relevant for dynamic assessment of food product performance during its life cycle. Based on this analysis, three means-criteria system diagrams for three functions, i.e., technology, marketing and consumer research, were developed and an integrated framework for dynamic assessment of new food product performance was presented. The means-criteria system diagrams can help decision makers to understand how individual means contribute to each function's performance criteria, as well as the overall performance of a product, i.e., sales. Additionally, the means-criteria system diagrams helped identifying the feedback loops, which are present, but mostly underappreciated in the analysis of new product performance. For instance, meeting quality specifications can be affected with loops contributing to product quality variation and technology synergy. Consumer satisfaction is altered through loops contributing to product familiarity, experienced product quality and positive beliefs from past tasting. Market share is influenced by feedback loops describing changes in market synergy and market potential. Inability to understand, monitor, and adjust performance variables in any of the identified feedback loops can contribute to lowered product sales and can ultimately lead to product failure over longer time.

The novelty of the framework is in its integrated perspective, which closely represents non-linearity and concurrence typical for the NPD process. Each function does not work in isolation. Change in performance of one function causes future changes in performance of other two functions and of the overall firm. The interconnections indicate the places where information exchange and communication is critical for improved product performance. The other value of the framework is in capturing the cyclic nature of the new food product performance in a single image. Such format facilitates fast navigation from one function to another by simply following arrows. Furthermore, it shows the cause-effect relationships between the actions of one function in a firm and consequences of these actions for that function, as well as for other functions.

The current study represents a limited view of the firm's performance, since it includes three functions, i.e., marketing, technology, and consumer research. Future studies could aim at expanding this boundary and could include other firm functions, e.g., sales, logistics, or production. This could result with the discovery of new feedback loops and causal connections, which could further increase understanding of the forces affecting food product performance on the firm level. Moreover, it is noteworthy to point out that in many real cases the exact dynamics of feedback loops and their effect on performance, such as actual sales or consumer satisfaction over time, is hard to correctly estimate with a qualitative means-criteria system diagram. Therefore, the next research step could include developing quantitative system dynamics models with Vensim or Stella software, to apply the knowledge gained from means-criteria system diagrams to specific product cases. Future research could focus on generating data appropriate for quantitative system dynamics models, according to the variables in the integrated framework. There is a need to establish time series data collection to detect changes over time, for example in consumer characteristics and consumer satisfaction, for a specific product. In some cases, there is also a need to define variables more comprehensively to fit the food domain, such as technology and marketing synergy, capability to implement change, capability to integrate information. With appropriate data, models for performance of specific food products could be developed to test future product strategies, in any stage of new product development and also during the product life-cycle.

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Appendix 1

Table A1.1. *Descriptions of variables of the means-criteria system diagrams from Figure 3.4 of the manuscript, with sources*

Variable	Description	Source*
Technology function		
Capability to implement changes	Capability to implement changes necessary to improve a product, and to reduce the risk of its failure.	2, 7
Extent of product optimization	Includes optimization of product characteristics, which can influence product's quality. Product characteristics are various physical features defining a product (e.g., appearance, texture, raw material used). They determine sensory characteristics of a product, and as such, are important for repurchase of a product by consumers. To optimize a product, identification of key ingredients, ingredient levels, and ideal sensory attributes is needed.	13, 18, 23, 26, 34
External decisions for product changes	Refers to any firm's changes in product's specification, which do not come from technology function, in terms of ingredients or processing of a product (e.g., due to changes in firm's objectives or suppliers).	37
Improvement in competitors' offerings	Improved competitors' offerings represent changes in competitors' products, which make those products more attractive to consumers.	4, 19
Improving firm's technology	Includes improvement in the current state of technology (e.g., the manufacturing process, ingredients, manufacturing equipment) a firm has access to in general, and not specific only to one product.	18, 32
Quality specifications met	A measure showing to what extent the product's characteristics correspond to the levels stated in the product's specification.	8, 11, 12, 17, 22, 25, 29
Primary products quality variation	Variations in the quality of primary products, or raw materials, may call for product optimization.	23
Product characteristics suitability	It represents the gap between the current product characteristics, and required product characteristics, due to the changed situation on the market, changes in firm's objectives or in the current state of firm's technology.	18, 36
Production equipment sensitivity	Sensitivity of production equipment can contribute to product quality variation. To meet quality specifications, product characteristics optimization may be required to reduce product variations due to equipment sensitivity.	23

Product newness	Product newness represents the degree of newness of technologies represented in a product. It can be increased, for example, by employing an innovative production process or by incorporating innovative ingredients, which deliver more benefits to consumers.	4, 9, 15, 17, 19, 20
Product quality variation	Variation in quality of the final product, resulting from modification of product characteristics or other variations, can have impact on experienced product quality by consumers.	23
Qualified skills allocation	This variable refers to the available in-house technical know-how, or the familiarity of the firm with the product, which can be increased by learning or hiring qualified staff.	2, 6, 7, 14, 19, 23, 32
Resources allocation	Represent allocation of the resources base of the firm needed to carry out a certain project. Technology resources can be labour force, such as the number of employees, or capital devoted to technology development activities or production efforts.	2, 7, 9, 14, 15, 20, 22, 32, 37
Technology synergy	Technology synergy represents the fit between the firm's resources and skills, and the needs of the project/product (in terms of R&D, engineering, and production, firm's objectives, and market demands).	2, 4, 6, 9, 13, 15, 16, 19, 22, 23, 27, 30, 32
Marketing function		
Capability to integrate information	The capability to generate, disseminate, and use market information to improve a product, and to reduce the risk of its failure.	25
Change in firm's objectives	Firm's objectives include strategic corporate objectives (e.g., change in firm's mission) or product platform objectives (e.g., solving a problem of cannibalization of firm's existing products).	7, 18, 19, 22, 27
Competitive response intensity	It reflects the intensity of competition in the marketplace in terms of likelihood of new competitors, and degree and intensity of response of competition to a new product introduction (e.g., in terms of price, quality, salesforce, and distribution system).	2, 6, 7, 9, 14, 15, 16, 17, 18, 22, 23, 27, 30, 35, 37
Distribution and sales synergy	Includes the type and amount of salesforce available, and appropriateness of distribution channels.	2, 4, 7, 17, 23
Market acceptance	Market acceptance is a measure that shows if a certain product is in sufficient demand - if it satisfies big enough customer/consumer base. This assures continued production, and availability of a product.	1, 16
Market characteristics variation	Market characteristics variation include market and demand size, and variation, customer need or demand level for a certain product, and trends. Markets are subsets of competing similar products, together with their potential customers. Variation in these characteristics have implications for product success.	1, 2, 3, 6, 14, 17, 23, 26, 19, 30, 35, 36

Marketing mix adjustment	Includes product alterations to maximize performance objectives (e.g., increased market share or sales). Marketing mix elements include product attributes, pricing, branding, advertising and promotion, and distribution.	2, 3, 5, 6, 7, 13, 17, 18, 19, 22, 23, 26
Marketing mix suitability	Marketing mix suitability includes suitability of product attributes, pricing, branding, advertising and promotion, and distribution in a marketplace. Product attributes are a dimension of a product defining consumers' perceptions. They are determined by the levels of product characteristics, and marketing mix elements, together with packaging as a communication vehicle. Advertising, and promotion decrease consumers' initial uncertainty about the product, and increase consumers' familiarity with the product. Marketing communications can also be aimed at strengthening the brand. The change in firm's objectives, market potential, or any other need for adjustment resulting from knowledge obtained through market research, can decrease marketing mix suitability, and can require modifications of the project/product.	2, 3, 4, 5, 6, 7, 9, 10, 13, 14, 15, 17, 18, 19, 20, 22, 23, 26, 27, 28, 31, 33, 35
Marketing synergy	Marketing synergy represents the fit between the firm's resources and skills, and the needs of the project in terms of integrating successfully market intelligence into new products and market communications. Increased marketing synergy leads to improved use of market information. It requires a certain level of marketing synergy to timely observe the changes in the fitness of the product to achieve desired goals.	6, 9, 15, 16, 19, 27, 32, 35
Market potential variation	Market potential is defined by the size of the market, and the need level of consumers for the product. The influence of variation in market potential needs to be understood, and monitored to assure good product performance.	2, 9, 13, 15, 19, 27, 32, 35
Market share	Percentage of volume sales of a product in a market.	6, 7, 10, 11, 12, 15, 17, 18, 19, 22, 23, 25, 28, 29, 30
Performing market research	Market research is undertaken to collect market information, such as market/consumer trends, or any other information describing the market, economic characteristics of an industry, or information about competitors. Extensive market research is executed to decrease consumer and competitor uncertainty.	2, 16, 19
Qualified skills allocation	To carry out marketing activities in an NPD project, a firm needs to possess a certain level of marketing skills. This includes general competences that exist in the firm resulting, for example, from learning from previous product launches or from the level of familiarity of a project/product to the firm.	6, 7, 23

Resources allocation	Marketing resources can be labour force, such as the number of employees, or capital devoted to marketing activities or market efforts, such as selling, and promoting a product.	2, 6, 7, 9, 15, 19, 22, 23, 25, 27, 32
Consumer research function		
Consumers' characteristics change	Consumers' characteristics influence consumers' behaviour. They include demographic data (gender, age), lifestyle data (household size), economic data, habits, consumer innovativeness (the degree of consumer receptiveness to new products), motivational aspects or changes in values (interest in healthy eating, convenience, environmental issues, and food safety).	1, 4, 5, 14, 18, 23, 26, 31, 33
Consumer satisfaction	Includes the extent to which product quality expectations are confirmed after consumption. More consumer satisfaction leads to more repeated purchase.	13, 14, 22, 23, 25, 26, 28
Experienced product quality	During consumption, consumers assess product's quality (e.g., product's taste or convenience). It is influenced by the existing quality expectations. One of the methods to measure it is hedonic liking.	13, 28
External reduction of consumer uncertainty	The more information consumers accumulate, the lower is the consumers' uncertainty about the product, which increases product familiarity. Activities such as word-of-mouth, and government and consumer organizations information campaigns can reduce consumers' uncertainty.	1, 4, 5, 14
Initial purchase/ initial purchase decision	Initial purchase intent assesses the probability of the first trial purchase. At this point product is new to a consumer, and the decision is based on consumers' product cues, and evaluation of product's advantage, compared to similar products. Initial purchase, and initial purchase decision are used interchangeably in this case.	13, 26, 28
Marketing mix suitability	Marketing mix suitability includes suitability of product attributes, pricing, branding, advertising and promotion, and distribution in a marketplace. Based on product attributes, and brand, consumers can, for example, assess product's convenience, quality, expected sensory properties, product's innovativeness, and satiety. Improvement or change of product attributes, if visible or communicated, can affect product quality perception cues. Advertising and promotion decrease consumers' initial uncertainty about the product, and increase consumers' familiarity with the product. Price can influence perception of product attributes, or even the utility derived from the product, and is assessed as the perceived price-performance congruency (value). Consumers use price as a predictor of quality, especially with less familiar products. It is often measured as willingness to pay (WTP).	2, 3, 4, 5, 6, 7, 9, 10, 13, 14, 15, 17, 18, 19, 20, 22, 23, 26, 28, 31, 33, 35
Perceived product advantage	Perceived product advantage is the extent to which consumers perceive a product superior, when compared to competing products, on account of its quality, function or cost-benefit ratio.	2, 4, 6, 9, 13, 15, 16, 19, 20, 25, 27, 32, 35

Product quality perception cues	Product quality perception is formed based on many factors available at the time of purchase, such as price, extrinsic attributes (information mentioned on the package), expected intrinsic quality (e.g., taste, health, convenience), or brand of the product.	5, 6, 13, 15, 18, 24, 26, 28, 33, 34, 35
Positive beliefs from past tasting	This is the accumulation of past satisfactory/unsatisfactory tasting experiences. Formed memories influence future purchases, instead of original tasting experiences.	5, 28
Product characteristics suitability	It represents the gap between the current product characteristics, and required product characteristics, due to the changed situation on the market, changes in firm’s objectives or in the current state of firm’s technology.	18, 36
Product familiarity	Represents the consumers’ awareness of the product. Reduced product familiarity, for example due to innovativeness of a product, can result with difficulty of determining product’s attributes. Increased product familiarity results from more product consumption or more information exposure.	3, 4, 18, 19, 25, 26
Product quality expectations	Product quality expectations are formed from perception of extrinsic quality cues, from the quality of the product promised by communication, and its physical appearance. Expectations are strongly related to consumer satisfaction.	6, 9, 13, 14, 15, 22, 25, 26, 27
Quality expectations of competitive products	Product quality expectations formed from perception of extrinsic quality cues of competitive products. They affect the perceived advantage of the firm’s product.	6, 9, 14, 15, 18, 25
Repeated purchase/repeated purchase decision	Repeated purchase denotes any future product purchase, after the initial purchase. Decision to repeat a purchase of a product is driven by beliefs about past fulfilment of experienced purchase motives, and product advantage compared to competing products. Repeated purchase, and repeated purchase decision are used interchangeably in this case.	13, 14, 26, 28
Shift in importance of product quality cues	Relative importance consumers assign to each product attribute defines utility derived from a product. The importance can vary between consumers, depending on their characteristics. Change in consumers’ characteristics can shift the relative importance of attributes, and affect the perceived product advantage.	1, 4, 5, 14, 18
Situational constraints	Situational constraints may represent consumers’ emotional states prior to purchase, availability of the product or other constraints, such as time, and money.	5, 18, 26

*references of sources are in Supplementary material 2

Chapter 4

Modifying the Bass diffusion model to study adoption of radical new foods – the case of edible insects in the Netherlands

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Abstract

Developing new food products is a complex process. Even if a company performs new product development activities successfully, it is still uncertain if the consumer will adopt the product. The Bass diffusion model has often been used to study product adoption. However, existing modifications of the Bass diffusion model do not capture the complexity of consumer food choice and they have limitations in situations where there is no sales data. To avoid these challenges, the system dynamics approach can be employed. This paper aimed at extending the existing system dynamics Bass diffusion model to investigate the dynamic adoption process of insect-based food from a consumer research perspective. We performed a structured review of the literature on edible insects to build the model. The model was used to study adoption of the product amongst consumers in the Netherlands. Simulations revealed that diffusion of a radical innovation, such as an insect-based burger, can proceed for many years before there are observable adopters in the total population, under the currently reported practices in the Netherlands. Expanding the awareness of this innovation requires many decades, which can be quickened by developing strategies aimed at increasing word-of-mouth. Nevertheless, the low likelihood to adopt such food remains a challenge towards full adoption, even when the sensory quality of products is improved. To fully explore how to improve the diffusion outcome of edible insects, more knowledge on mechanisms related to positive and negative word-of-mouth, and adoption of insect-based burgers by people who initially reject them, is needed. Our study demonstrated that system dynamics models could have potential in designing new food product strategies in companies, as they facilitate decision-making, and uncover knowledge gaps.

1. Introduction

Development of new food products is one of the most important activities in food companies, as successful new products contribute substantially to the growth of a company (Huang et al., 2015). Even if a company performs new product development (NPD) activities successfully, it is still uncertain if a product will be adopted among consumers, which makes NPD a risky process (Huang et al., 2015). NPD is a complex process, since various company functions (e.g., marketing, R&D, sales, production, etc.) need to work together to establish product attributes, produce the product, and launch it on the market (Earle et al., 2001). Moreover, additional complexity arises due to changes in consumers' needs and preferences, which are a result of a multitude of person-, product- and environment-related factors (Kim and Wilemon, 2003). These factors enhance uncertainty whether consumers will adopt a particular product. Since consumers have the final verdict in the new product adoption, understanding their needs and preferences has been a recommended approach towards successful NPD (Dijksterhuis, 2016).

Researchers have been using various tools and measures that facilitate understanding of consumers' preferences for food products (see Sogari et al. (2018) for a review of tools and methods). For example, researchers have been studying, amongst others, consumers' "purchase intent", "willingness to try", and "food neophobia" (e.g., review by Damsbo-Svendsen et al. (2017)). These tools aim at studying a multitude of person-related factors (psychological factors and socio-demographic characteristics) and food product attributes in relation to consumers' food choice. Measures like "willingness to try" and "purchase intent" give invaluable guidelines to develop effective product design and product positioning strategies. These types of approaches increase the understanding of product adoption from a "detail complexity" perspective, which is a complexity where a large number of variables and their interconnections are considered (Grösser, 2017). However, these approaches give limited insight in the evolvement of product success over a longer period (Repenning, 2002), as they do not consider consumer product adoption from a dynamic perspective. Therefore, focusing on "dynamic complexity", instead of "detail complexity", can reduce the number of variables needed to facilitate understanding of NPD strategies that could lead to product adoption, and ultimately, to sustainable product success over time (Martin, 2013).

There has been a stream of research dedicated to studying product adoption from a dynamic perspective, i.e., if a product will be adopted over time, stemming from the diffusion of innovations paradigm. The diffusion of innovations (DoI) paradigm has been established as a common way of researching the spread of a new product in the marketplace (Goldenberg and

Shapira, 2009). In the 1960s, DoI was used to develop the mathematical Bass diffusion model, which was employed to analytically study new product adoption on the market (Sterman, 2004; Bass, 1969). The original Bass diffusion model consisted of a limited number of variables, and the decades following its development saw a rise of literature dedicated to expanding it (e.g., Mahajan et al., 1990). However, the Bass diffusion model requires sufficient sales data (e.g., of the existing or analogous product) to the estimate model parameters (Meade and Islam, 2006). Obtaining data of processed foods can be particularly challenging, especially in situations when a new to the world food product (e.g., radical food such as edible insects) is being developed and no similar products exist on the market that could be used to estimate the parameters of the analytical Bass diffusion model (House, 2016; Duval and Biere, 2002). In such situations, simulation modeling can be useful to study complex problems, such as product adoption over time (Borshchev and Filippov, 2004).

The adoption process is a problem that has commonly been approached by a simulation modelling approach called system dynamics (SD). System dynamics simulation models focus on dynamic complexity, wherein one looks into causal relationships between variables, which lead to different types of behaviour over time. Instead of using only sales data to estimate model parameters, other appropriate data can be used to formalize the model, such as data on customer choices (e.g., Schmidt and Gary, 2002). SD modelling is a way to simplify reality, making it easier to comprehend, with the purpose of testing possible consequences of various strategies (Sterman, 2004), such as promotion intensity or product quality level. SD models are not predictive, but descriptive models (Barlas, 2009; Sterman, 2004; Ford, 1999). One chooses to build an SD model when the aim is to improve general understanding of a dynamic problem by studying the patterns of change (i.e., the shapes of the curves over time that result from many different model simulations) and to identify knowledge gaps to guide future research efforts (Ford, 1999). SD, coupled with the diffusion of innovations paradigm, has been used to study a wide range of adoption problems (e.g., improved maize seed (Derwisch et al., 2016), alternative fuel vehicles (Benvenutti et al., 2017), cell-phones (Dutta et al., 2017), renewable energy (Jimenez et al., 2016), golf clubs (Kreng and Wang, 2013), application of a product adoption model for pricing strategy (Milling, 1996), medical technologies (Homer, 1987)). However, to the best of our knowledge, the SD approach has not been adopted to study the adoption of radical new foods by consumers.

With this paper, we aimed at extending the existing SD Bass diffusion model to develop and simulate adoption of a radical new food product, i.e., an insect-based burger. Currently, the Netherlands have been at the forefront of insect-based food business in the Western world

(Jansson and Berggren, 2015; Pascucci and de-Magistris, 2013), where insect-based food has been promoted since the late 1990s (de-Magistris et al., 2015). For example, in Dutch supermarkets, burgers containing up to 15% of ground insects are sold regularly (Glover and Sexton, 2015; Shelomi, 2015). However, the concern if people are ready to adopt such a radical innovation remains. Therefore, we focused on the topic of insect-based burgers in the Netherlands to investigate the possibility of the SD approach to capture and study the dynamic diffusion process of radical food innovation among consumers, and to identify knowledge gaps that could guide future research.

2. Theoretical background

Since the diffusion of innovations paradigm and the Bass diffusion analytical model are the foundation for complexity modelling of new product diffusion (Goldenberg and Shapira, 2009; Sterman, 2004; Bass, 1969), we used them to explore the topic of insect-based food adoption in the Netherlands.

2.1. The diffusion of innovations paradigm (DoI)

The diffusion of innovations (DoI) paradigm is the social process of communicating a subjective evaluation of an innovation from person to person (Rogers, 2003). The outcome of the diffusion of an innovation is plotted as a cumulative number of adopters over time, in which case the plotted curve reveals an S-shaped growth (Delre et al., 2007; Sterman, 2004; Rogers, 2003).

DoI consists of four main elements: 1) an innovation, 2) communication of the innovation through a certain channel, 3) the time over which this happens, and 4) a social system in which this occurs. An innovation is characterized by its newness to an individual, and not by its newness to the world. Communication channels are means of exchanging information about an innovation between an individual who has knowledge of, or experience, with the innovation, and an individual who has no knowledge or experience with it (Jimenez et al., 2016). Diffusion occurs over a certain time, which is needed for individuals to communicate through the channels (Frattini et al., 2014; Mahajan et al., 1990). Lastly, these individuals are part of a social system with certain boundaries, within which innovation diffusion occurs (Rogers, 2003). The time an individual takes to go through the process of adopting an innovation is affected by perceived attributes of the innovation, communication channels (e.g., mass media, interpersonal), the nature of the social system (e.g., norms), the extent of promotion efforts, and the type of innovation-decision (Rogers, 2003). Innovation decisions are distinguished based on who makes the decision and if it is made freely. There are three types of innovation-decisions: optional (made by an individual), collective (made collectively), and authority (made by individuals in positions of power for the entire social system) (Rogers, 2003).

2.2. Theoretical background on the Bass diffusion model of innovation adoption

There is an extensive body of literature on diffusion of innovations in the marketing field. The main catalyst of this development was a new product growth model developed by Bass (Mahajan et al., 1990; Bass 1969). The original Bass diffusion model has a fixed population of potential adopters and it assumes that they are influenced by mass media and word-of-mouth communication, which are affected by the coefficient of innovation, and the coefficient of imitation, respectively. These coefficients are estimated from existing sales data of a product, or by using historical sales data of an analogous product. The original Bass diffusion model underwent multiple extensions in the last decades. For example, marketing mix variables (e.g., price, advertising, distribution), change in market potential over time due to the growth in households and population, the number of retailers selling the product, or income distribution have been considered (Meade and Islam, 2006; Mahajan et al., 1990). Moreover, additions like supply restrictions, impact of market and product characteristics, and adoption of successive generations of products have been noted (Mahajan et al., 1990).

The Bass diffusion model is also common in the SD field, since it has been translated from its algebraic form to the SD form. System dynamics is a methodology to study complex problems, which have two main characteristics. Firstly, the problems are dynamic; they involve quantities that change over time, which can be expressed as graphs of variables over time (Richardson and Pugh III, 1981). Secondly, the problems involve the notion of feedback (Richardson and Pugh III, 1981). The main sources of dynamics in a system are cause-effect relationships between variables in the system, in the form of reinforcing and/or balancing feedback loops (Sterman, 2004; Richardson and Pugh III, 1981). SD models are used to study patterns of behaviour or graphs of variables over time, and not for point prediction. They are descriptive models that allow comparison of the difference in patterns of behaviour among various scenarios (Barlas, 2009; Sterman, 2004; Ford, 1999).

The SD Bass diffusion model distinguishes two feedback mechanisms, namely market adoption or adoption through mass media (external influence) and word-of-mouth (internal influence) (Milling and Maier, 2009; Sterman, 2004; Mahajan et al., 1990). They act as two

different communication channels. The external influence serves the purpose of “seeding” the market with early adopters, who then initiate word-of-mouth in the population among potential adopters (Morecroft, 2007). The Bass diffusion model represents adoption of an innovation among members of a closed system (Sterman, 2004; Bass, 1969). It belongs to the group of aggregate models where consumers are studied as a perfectly mixed collection of individuals with an aggregated behaviour, instead of representing individual behavioural characteristics of consumers (Yücel and van Daalen, 2011; Goldenberg and Shapira, 2009). Therefore, numerical values of variables correspond to average values of the whole social system that is studied. The dynamic behaviour of the basic Bass diffusion model is represented by the S-shaped growth curve of a cumulative number of adopters over time, which is also characteristic for DoI.
Although both the marketing and SD field have a long tradition of research based on the Bass diffusion model, the existing model adaptions do not support studying adoption of a radical food product by consumers. There has been a concern about the applicability of the hypotheses from the general diffusion research to consumer behaviour (Gatignon and Robertson, 1985). Food choice is affected by changes in consumers’ needs and preferences, resulting from a multitude of person-, product and environment-related factors (Kim and Wilemon, 2003). The majority of marketing diffusion of innovations research is on consumer durables and telecommunications (e.g., review by Meade and Islam (2006); and the authors of this chapter performed a review of scientific papers on the Bass diffusion model on Scopus from 2005 until 2019). Moreover, adoption of new foods by consumers has also not been studied with the SD approach. Therefore, there is a need to adapt the Bass diffusion model to the current literature on consumer adoption of insect-based food. Furthermore, since sales data to estimate parameters for the analytical Bass diffusion model are not available (House, 2016), this paper aims at adapting an SD Bass diffusion model.

2.3. Conceptual framework for insect-based food adoption, resulting from theoretical background

Based on the DoI paradigm and the Bass diffusion SD model, a conceptual framework (Figure 4.1) was developed to analyse current insect-based food adoption literature and to extend the existing SD model for adoption of insect-based food. The conceptual framework in Figure 4.1 has four stocks (“Potential adopters”, “Potential tasters”, “Adopters”, and “Rejecters”) and five flows (“potential tasting rate”, “adoption rate”, “rejection rate”, “adoption rate 2”, and “rejection rate 2”). Stocks represent accumulations of the Dutch population in different adoption phases. Flows represent the rates with which people move from one stage of the decision process to another. The flows are determined by any of the four main factors: perceived attributes of innovation, communication channels, nature of the social system, and promotion efforts. The framework in Figure 4.1 is developed from a consumer perspective, which implies an optional innovation-decision type, where decisions are not made collectively, but by individuals (Rogers, 2003).

The basic Bass diffusion model has only two stocks and one flow ("Potential adopters", "Adopters", and "adoption rate"). However, DoI suggests that people usually become adopters or active rejecters of an innovation only after they have had a chance to try it (Rogers, 2003). Therefore, two more stocks were added to make a distinction between people who merely decide to try insect-based burgers and the ones who decide to adopt it as part of their diet, or reject it, after tasting it. The stock of "Potential tasters" represents the population willing to try insect-based food. The stock of "Adopters" corresponds to the population that is likely to adopt a certain insect-based product after tasting it. In this respect, it is worth to notice that according to Tan et al. (2016) more than 20% of Dutch consumers have tasted insects in past situations.

3. Building the model

In this study, building the SD model is divided into two stages: 1) a qualitative, including literature review to develop an SD model structure, and 2) a quantitative, to formulate and test the model. The model was built using Vensim DSS software, Version 6.4b (2018). Literature on insect-based food consumption among Westerner consumers was used in the qualitative stage, i.e., the model conceptualization. Qualitative research is commonly used as a valuable information source in SD, as it represents a larger source of information compared to numerical data (Forrester, 1992). In the quantitative stage, i.e., model formulation, existing empirical studies with Dutch consumers were employed, with a special focus on insect-based burgers studies, to confine the assumptions to only one social system. If no appropriate datasets were available for Dutch consumers, quantitative data were obtained from studies on Flemish consumers. All variable formulations and sources of data are in Tables 4.1 and 4.2, while additional information on data, which was used to formulate equations, is in Supplementary material 3, Table S3.1.

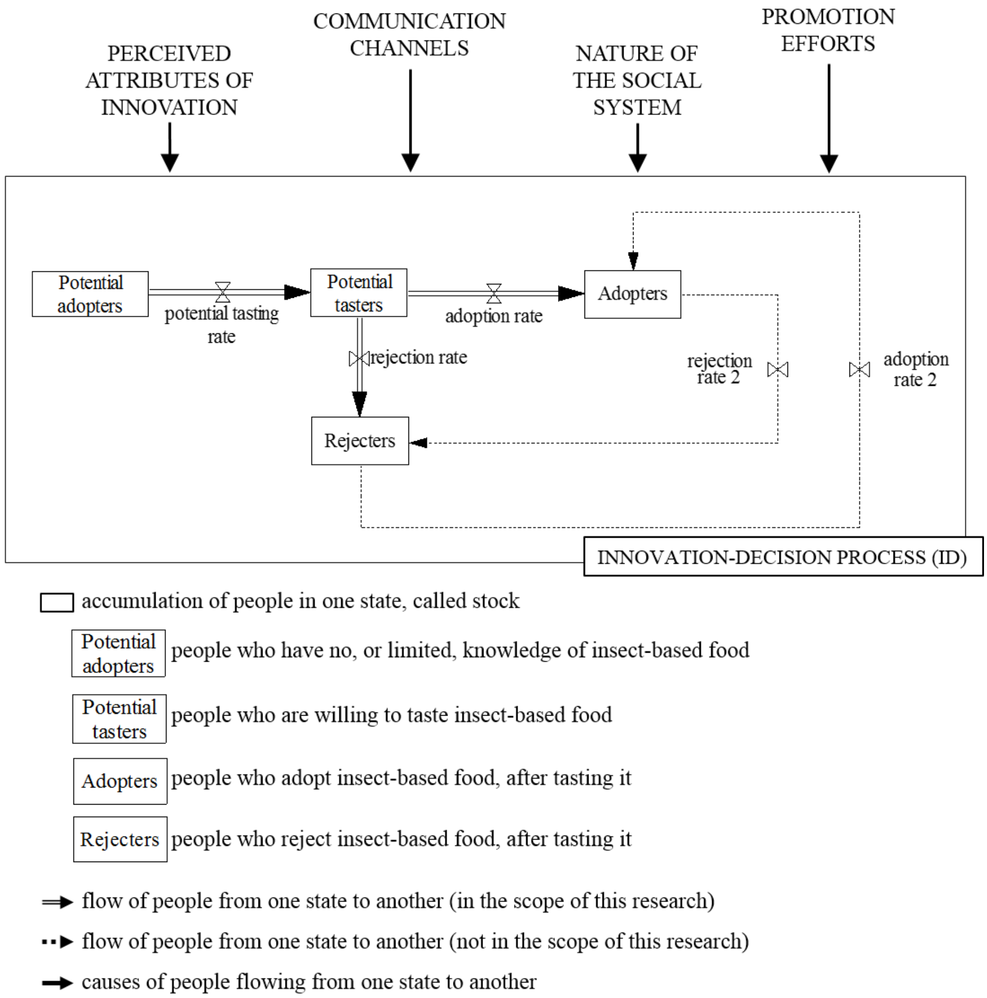


Figure 4.1. *Framework to analyse insect-based food adoption literature and to build the model, based on the diffusion of innovations paradigm (Rogers, 2003) and the Bass diffusion system dynamics model (Sterman, 2004).*

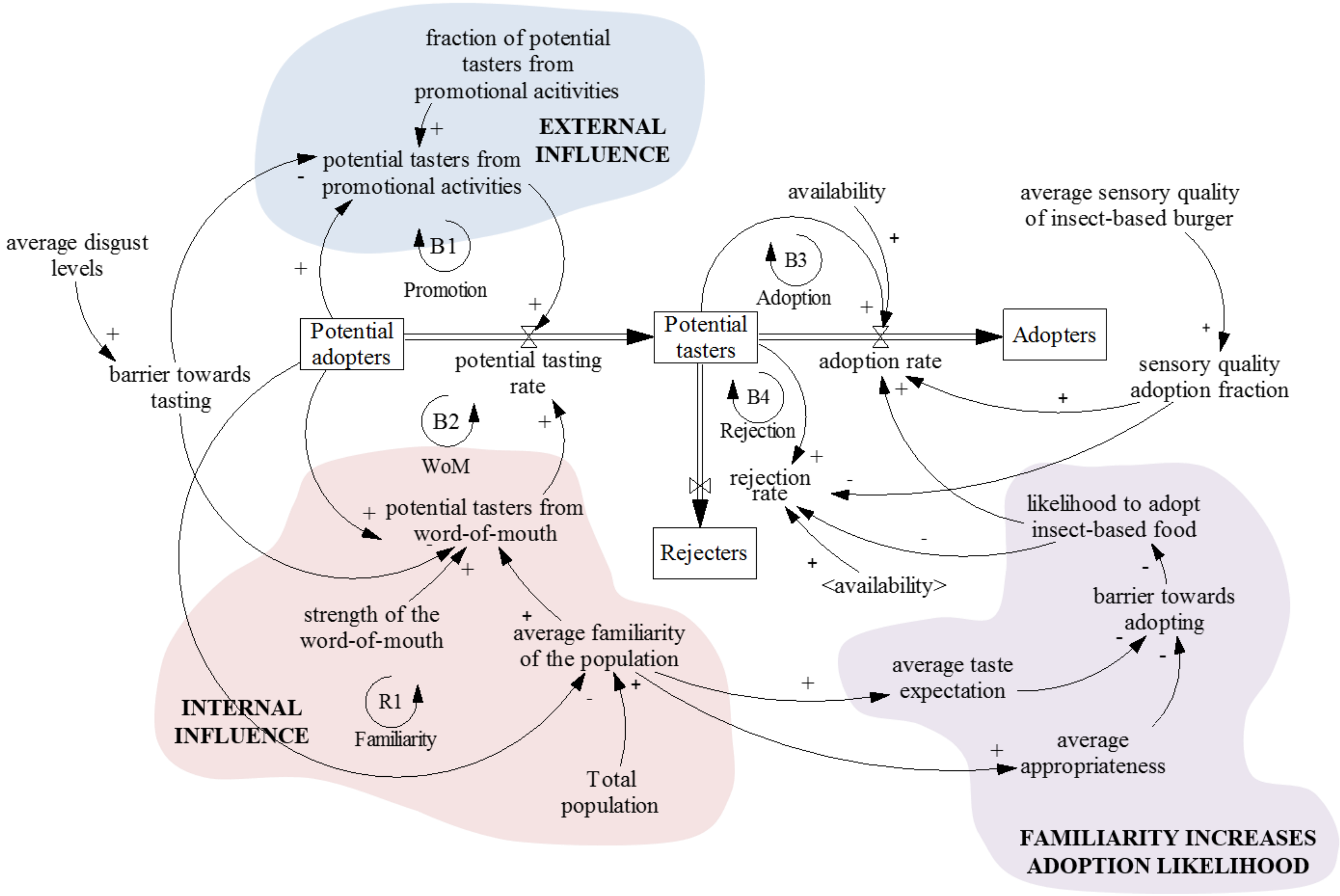
3.1. Developing the conceptual model (stock and flow diagram)

The proposed framework (Figure 4.1) shows the boundary of the system, which was used for the literature review on insect-based food adoption to uncover relevant variables and their causal relations. More specifically, the boundary of the system is defined by the innovation-decision process (ID), as the backbone of the model, and the four factors - perceived attributes of innovation, communication channels, nature of the social system, and promotion efforts. As such, the model represents an overview of factors relevant under the proposed framework, with the focus on variables that affect the system dynamically.

3.1.1. From potential adopters to potential tasters

Figure 4.2 shows the stock and flow diagram of insect-based food adoption in the Netherlands. The structure of the model from “Potential adopters” to “Potential tasters” represents the process of deciding to taste insect-based food, and it is the first step towards adopting insect-based burgers. The ID starts with external influence on “Potential adopters”. Commonly reported external influence in insect-based food literature is promotion in the form of direct education campaigns, such as bug banquets (Hamerman, 2016; Looy and Wood, 2006), together with other mass media promotional activities (Sterman, 2004; Rogers, 2003). They “seed” the system with “potential tasters from promotional activities”, who will spread the word-of-mouth (WoM) about an innovation (Pitt et al., 2014; Sterman, 2004), and so will initiate the internal influence. The more people have a chance to learn about insects through external influence, the more they spread WoM among people who had no experience with the new food (Shelomi, 2015), which increases the “average familiarity of the population”. For internal influence to have effect, potential adopters need to be able to find the product to decide to taste it for the first time, which is a frequently mentioned obstacle towards acceptance of edible insects (Shelomi, 2015, van Huis et al., 2013; Schösler et al., 2012; Looy and Wood, 2006). Furthermore, not every contact with “Potential adopters” will be fruitful. Consequently, the amount of “potential tasters from word-of-mouth” depends on the “strength of the word-of-mouth” variable.

Nevertheless, merely exposing people to such food does not imply they will decide to taste it, due to negative feelings associated with insect-based food (Balzan et al., 2016). Negative feelings associated with tasting unappealing food, such as insects, can be divided in three dimensions: expectations of bad sensory properties (distaste), expectations of harmful consequences (danger or risk), and disgust (Hamerman, 2016; Balzan et al., 2016; Martins and Pliner, 2005). However, disgust is one of the major predictors of willingness not to taste (Balzan et al., 2016; Martins and Pliner, 2006), representing the main “barrier towards tasting” insect-based food for the first time in the model. In practice, disgust can be altered by the visibility of insects in the food, since decreased visibility had a positive influence on reducing the barrier to trying insect-based food (Shelomi, 2015; Verbeke, 2015; Caparros Megido et al., 2014).



fraction of potential tasters from promotional acitivities
EXTERNAL INFLUENCE
potential tasters from promotional activities
B1
Promotion
average disgust levels
barrier towards tasting
Potential adopters
potential tasting rate
Potential tasters
adoption rate
Adopters
availability
B3
Adoption
average sensory quality of insect-based burger
sensory quality adoption fraction
B2
WoM
B4
Rejection
rejection rate
Rejecters
potential tasters from word-of-mouth
strength of the word-of-mouth
average familiarity of the population
likelihood to adopt insect-based food
<availability>
barrier towards adopting
average taste expectation
average appropriateness
R1
Familiarity
INTERNAL INFLUENCE
Total population
FAMILIARITY INCREASES ADOPTION LIKELIHOOD

Figure 4.2. *Stock and flow diagram of insect-based food adoption in the Netherlands. The rate with which "Potential adopters" become "Potential tasters" of insect based food depends on external influence and internal influence on "Potential adopters". The rate with which "Potential tasters" become "Adopters" or "Rejecters" depends on their familiarity with insect-based food, which increases adoption likelihood, and on the average sensory quality of insect-based burger.*

(Legend: positive causal influence – other things being equal, an increase in variable A causes an increase in variable B, or a decrease in variable A causes a decrease in variable B; negative causal influence – other things being equal, an increase in variable A causes a decrease in variable B, or a decrease in variable A causes an increase in variable B. Meaning of variables in < >: the variable is copied to avoid decluttering the image with arrows and it is defined elsewhere in the model. B balancing feedback loop, R reinforcing feedback loop).

3.1.2. From potential tasters to adopters or rejecters

Figure 4.2 physically separates people who are willing to taste insect-based food in general ("Potential tasters") from the ones who are likely to adopt insect-based burgers once they appeared on the market in the Netherlands ("Adopters"). To adopt a certain food, people need to taste it first (Ruby et al., 2015). Trying the food facilitates learning to like the food and can have an influence on the overall adoption (Shelomi, 2015; Tan et al., 2015) by increasing familiarity with a certain food through reduction of uncertainty (Tan et al., 2016). Increasing the overall familiarity with insect-based food can result in future increased adoption likelihood (Hamerman, 2016; van Huis, 2016; Hartmann et al., 2015). Increasing familiarity of the whole population with insect-based food ("average familiarity of the population") may partially lead to lowering the barrier towards adopting it (Balzan et al., 2016).

Achieving familiarity with food through a tasting experience enables a more accurate prediction of perceived sensory properties of food (Tan et al., 2015), which could decrease the chances of coming to wrong inferences about the product's sensory characteristics ("average taste expectations)" (Tan et al., 2016). On the other hand, exposure to food has an effect on increasing "average food appropriateness", which facilitates the change of culturally embedded assumptions about inappropriate foods such as insects (Tan et al., 2016). Moreover, for adoption of an insect-based food to occur, it is important that the specific insect-based food product tastes good (Schouteten et al., 2016; Hartmann et al., 2015; Tan et al., 2015; Schösler et al., 2012). Therefore, the "average sensory quality of insect-based burger" directly influences the adoption rate and an extremely negative tasting experience may result in complete rejection of the food (Tan et al., 2016; Hartmann et al., 2015). Lastly, for adoption to be possible, it is necessary that the insect-based burger is available on the market. The variable "availability switch" allows the adoption of insect-based burgers only from the beginning of 2015, once they appeared on the market.

It is important to mention that the model is based on some assumptions that can notably affect the end result of adoption. Firstly, it is assumed that people, who have once tasted insect-based products, will eventually make a decision towards adopting or rejecting such food. In reality, people might try edible insects multiple times before making the final decision, or even never make the decision. Furthermore, some people might never even taste insect-based food, for example, due to dietary restrictions (e.g., allergies). Secondly, the "average sensory quality of insect-based burger" is the average sensory liking estimated based on two studies. Schouteten et al. (2006) performed research on sensory liking of an insect-based burger with no added meat, and Tan et al. (2016) studied ground beef and ground mealworm burgers. The shape and content of the products in these two studies is not the same, which could have made a difference in a respondent's assessment, but the studies consistently reported low sensory liking. Moreover, some common marketing factors, such as influence of brand, competition, image or price are omitted from the model in Figure 4.2, since Sterman (2004) recommends to separate the flow of adoption from the flow of purchase.

Furthermore, some variables that literature on edible insects mentioned have been purposefully omitted from the model in Figure 4.2. Although advertising nutritional and environmental benefits of a product has been a frequent strategy to convince people into adopting them, it has been shown insufficient many times (Tan et al., 2016; Verbeke, 2015; Loo and Sellbach, 2013; Derkzen, 2011). Therefore, this strategy was not included in the model, which puts the focus on the taste of insect-based burgers (Schouteten et al., 2016; Tan et al., 2015). Moreover, food neophobia has been used in investigating acceptance of insect-based food. However, scientists have divided opinions regarding food neophobia and its direct influence on insect-based food acceptance. Tan et al. (2016) claimed that food neophobia plays a minor role in the case of unusual foods such as insects. Hartmann et al. (2015) stated that, regardless of food neophobia, the strongest predictor of willingness to eat insects was perceived taste. Nevertheless, food neophobia is indirectly present as the model contains data on product appropriateness and taste expectations of consumers (Tan et al., 2016).

3.2. Model formulation and testing

After designing the stock and flow diagram, we developed equations based on the Bass diffusion SD model (Sterman, 2004), literature on SD (Richardson and Pugh III, 1981), and data from reviewed literature on edible insects. Table 4.1 contains the equations of stocks, flows, and auxiliary variables, together with their definitions, units, and formulas, with the sources on which assumptions and adaptations were made. Table 4.2 lists the constant variables and their estimated values as used for the base run simulation (simulation with data extracted from and fitted to the literature sources).

Model testing involved model verification and validation to uncover errors and to build confidence in its usefulness. Model verification was performed to test if the model was incorrectly coded or simulated, by checking equations, unit consistency (dimensional analysis), and numerical errors as a result of inappropriate numeric integration and step size (Pruyt, 2013). Model validation included sensitivity analysis, theoretical structure verification, and extreme conditions tests (Sterman, 2004; Barlas, 1994) (see Supplementary material 3 for explanation). Sensitivity analysis included studying the effect of small changes in parameters and functions on model behaviour in order to look for model errors, to understand relationships between inputs and emergent behaviour, and to identify highly sensitive inputs (Pruyt, 2013). The extreme conditions test included the evaluation of the model equations under extreme conditions (Barlas, 1994). Theoretical structure verification tested if the model structure is consistent with knowledge about the system (Pruyt, 2013). This was assured by performing a structured literature review.

Most of the values of auxiliary and constant variables are based on theories and data grounded in the SD and edible insect literature. However, we made some assumptions (see Table 4.1 and Table 4.2), due to a lack of available data on insect-based food adoption. "Fraction of potential adopters from promotional activities" and "strength of the word-of-mouth" are variables with assumed values. These variables have an influence on the value of "average familiarity of the population". They determine the number of people in the system who had the opportunity to taste insect-based food. The numerical values of these variables have been adjusted in such way that the system reaches a value of average familiarity of approximately 20% in the year 2015 (Tan et al., 2016). Secondly, values of both variables were adjusted for the cumulative internal influence (number of "Potential tasters" in the end of the simulation as a result of internal influence) to be approximately ten times bigger than the cumulative external influence (number of "Potential tasters" in the end of the simulation as a result of external influence)(Goldenberg and Shapira, 2009).

Table 4.1. *Stock, flow, and auxiliary variables of the insect-based food adoption model – Vensim formulations and assumptions with sources**

Variable	Definition	Unit	Formulation	Source
STOCKS				
Potential adopters	People in the Netherlands who eat meat containing diets	people	= ∫-potential tasting rate dt + [Total population]	Formula adapted from Sterman (2004)
Potential tasters	People in the Netherlands who are likely to taste insect-based food	people	= ∫potential tasting rate - adoption rate - rejection rate dt + [0]	Formula adapted from Sterman (2004)
Adopters	People in the Netherlands who are likely to adopt an insect-based burger after tasting	people	= ∫adoption rate dt + [0]	Formula adapted from Sterman (2004)
Rejecters	People in the Netherlands who are likely to reject an insect-based burger after tasting	people	= ∫rejection rate dt + [0]	Formula adapted from Sterman (2004)
FLOWS				
potential tasting rate	Number of people tasting insect-based food for the first time per year	people/Year	= "potential tasters from word-of-mouth" + potential tasters from promotional activities	Formula adapted from Sterman (2004)
adoption rate	Number of people likely to adopt the product per year	people/Year	= Potential tasters*"likelihood to adopt insect-based food"*sensory quality adoption fraction*availability	Based on Hartmann et al. (2015), Verbeke (2015), and Martins and Pliner (2005)
rejection rate	Number of people likely to reject the product per year	people/Year	= (1-sensory quality adoption fraction)*Potential tasters*(1-"likelihood to adopt insect-based food")*availability	Based on Balzan et al. (2016), Tan et al. (2016), and Tan et al. (2015)
AUXILIARY VARIABLES				
average familiarity of the population	Average familiarity of the total population with insect-based food, based on the fraction of people who tasted it	Dmnl	= (Total population - Potential adopters)/Total population	Formula adapted from Sterman (2004)
barrier towards adopting	Average barrier towards adopting insect-based food, among the total population, as a result of the sum of average taste expectation and average appropriateness, values from 0 to 1 (value 0 – full barrier; value 1 – no barrier)	Dmnl	= 1-(average taste expectation/2+average appropriateness/2)	Based on Baker et al. (2016) and Tan et al. (2016)
potential tasters from promotional activities	Number of potential adopters who are likely to taste insect-based food as a result of promotional activities each year	people/Year	= Potential adopters*barrier towards tasting*fraction of potential tasters from promotional activities	Based on Hamerman (2016) and Looy and Wood (2006)
potential tasters from word-of-mouth	Number of potential adopters who are likely to taste insect-based food as a result of word-of-mouth effect each year	people/Year	= (Potential adopters*"strength of the word-of-mouth"*average familiarity of the population)*barrier towards tasting	Formula adapted from Sterman (2004)

AUXILIARY VARIABLES “WITH LOOKUP”				
average appropriateness	Average appropriateness of insect-based food of the total population; based on average familiarity of the population with insect-based food	Dmnl	= WITH LOOKUP (average familiarity of the population, ([(0,0)-(1,1)], (0,0.01), (0.5,0.67), (1,0.72)))	Based on Tan et al. (2016)
average taste expectation	Average taste expectation of insect-based food of the total population; based on average familiarity of the population with insect-based food	Dmnl	= WITH LOOKUP (average familiarity of the population, ([(0,0) - (1,1)], (0,0.28), (0.5,0.44), (1,0.56)))	Based on Tan et al. (2016)
barrier towards tasting	Barrier towards tasting insect-based food as a result of average disgust levels of the population, from 0 to 1 (with assumptions: value 0 – full barrier; value 1 – no barrier)	Dmnl	= WITH LOOKUP (average disgust level, ([(0,0) - (1,1)], (0,1), (0.32,0.93), (1,0))	Based on Schouteten et al. (2016)
likelihood to adopt insect-based food	Likelihood to adopt insect-based food, as a result of the barrier towards adopting, from 0 to 1 (with assumptions: value 0 – no barrier, full adoption; value 1 – full barrier, no adoption). Assumption is an averaged value of literature reported values.	Dmnl	= WITH LOOKUP (barrier towards adopting, ([(0,0) - (1,1)], (0,1), (0.55,0.12), (1,0)))	Based on Tan et al. (2016), Tan et al. (2015), and Verbeke (2015)
sensory quality adoption fraction	Fraction of population adopting insect-based burger based on liking its sensory characteristics, from 0 to 1 (value 0 – no adoption; value 1 – full adoption)	1/Year	= WITH LOOKUP ("average sensory quality of insect-based burger", ([(0,0) - (1,1)], (0,0), (0.125,0), (0.6,0.5), (0.875,1), (1,1))	Based on Schouteten et al. (2016), Tan et al. (2016), and Schösler et al. (2012)

*Model settings: time step: 0.125, integration type: RK4 Auto, units for time: Year.

Table 4.2. *Constant variables of the insect-based food adoption model, with values used for the base run*

Variable	Definition	Unit	Formulation	Source
availability	Variable that represents availability of insect-based burgers in the Netherlands, with value 0 before year 2015 and value 1 from year 2015	Dmnl	= STEP (1, 2015)	Assumption based on Glover and Sexton (2015)
average disgust level	The average level of disgust of the population when in the situation of tasting insect-based food, from 0 (no disgust, 100% chances of tasting) to 1 (100% disgust, 0% chances of trying)	Dmnl	= 0.32	Based on Hartmann et al. (2015)
average sensory quality of insect-based burger	Average sensory liking of an insect-based burger and insect-based meatballs, normalized to 0-1 data range.	Dmnl	= 0.54	Based on Schouteten et al (2016) and Tan et al. (2016)
fraction of potential tasters from promotional activities	Fraction of potential adopters exposed to promotional activities of insect-based food	1/Year	= 0.0036	Assumption based on Goldenberg and Shapira (2009)
strength of the word-of-mouth	Probability that the contact with Potential adopters will result with fruitful word-of-mouth	Dmnl	= 0.151	Assumption based on Goldenberg and Shapira (2009)
Total population	Total model population representing people in the Netherlands expected to have meat eating diets. Based on the total population of the Netherlands in the year 2015 (16900720) minus 4% people with special eating habits (e.g., vegetarian, vegan, macrobiotic, anthroposophical)	people	= 16900720-(16900720*0.04)	Based on CBS StatLine (2017), van Rossum et al. (2016), and Dagevos et al. (2012)

4. Model analysis

4.1. Base run model simulation

Figure 4.3 represents the behaviour of the simulated model and it shows changes in the stock values from the year 1998 to 2048. Promotion of insect-based food in the Netherlands started in the late 1990s (Dicke et al., 2014). Since the exact year cannot be precisely determined, the year 1998 has been chosen to represent the start of the simulation. The model shows 50 years of insect-based food adoption, until the model base run approaches steady state. The same as the original Bass diffusion model (Sterman, 2004), this model does not include population change in the Netherlands in the period from 1998 to 2048. This assumption was made for simplification reasons and is considered valid due to the qualitative interpretation of SD model results, where the exact values of stocks in the end of the model run are not as important as the shape of the curves (Sterman, 2004).

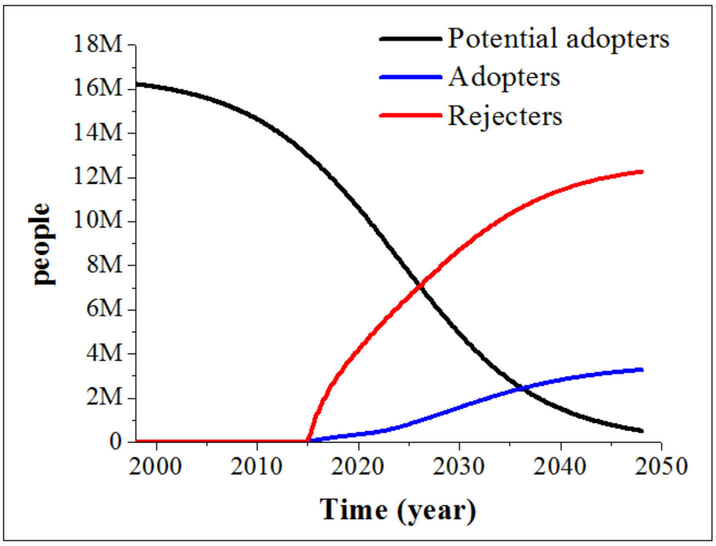


Figure 4.3. *Base run model behaviour showing changes in the main stocks of the model on insect-based food adoption in the Netherlands.*

Figure 4.3 shows that the diffusion process of insect-based food is slow in the beginning. The stock of "Potential adopters" depletes slowly. External influence, such as promotional activities of insect-based food, is the main mechanism that drives depletion of the stock of "Potential adopters" in the beginning (Sterman, 2004). A fixed number of people have the opportunity to become familiar with insect-based food each year through these activities, which slowly increases the number of "Potential tasters". "Potential tasters", in turn, increase the chance of the word-of-mouth (WoM) adoption, by raising the variable "average familiarity of the population” and by increasing the probability of contact with “Potential adopters”. Internal influence, or the effect of WoM, gains strength over time and becomes the main adoption mechanism, contributing to the increased speed of depletion of the stock of “Potential adopters” from around year 2010 (Sterman, 2004). As the stock of “Potential adopters” depletes towards the year 2048, both mechanisms lose on their strength because of a lack of new “Potential adopters” in the system. Almost everybody is familiar with insect-based food by the year 2048.

Once insect-based burgers become available on the market, stocks of “Adopters” and “Rejecters” start filling with people who are familiar with and who tasted insect-based burgers. A high number of people in the stock of “Rejecters”, and a low number of people in the stock of “Adopters” at the end of the simulation, show that the overall adoption is not very high. Adoption is partially influenced by “likelihood to adopt the product”, which is a result of “average taste expectation” and “average appropriateness” of insect-based food among the population, as experienced in previous tasting opportunities. The higher the average familiarity of the population is, the higher is the likelihood to adopt such food. Although an increase in average familiarity has a positive influence on the overall likelihood to adopt (Tan et al., 2016), its value is low throughout the whole simulation, which shows deeply embedded barriers towards insect-based food (Baker et al., 2016, Yen, 2009).

Moreover, on top of the low likelihood to adopt, rejection based on “average sensory quality of insect-based burger” is a second challenge of the adoption process. At this point, sensory properties of insect-based burgers are still not competitive to the meat-containing burgers, which are usually the reference point when deciding upon such a product’s taste (Schouteten et al., 2016). Positioning insect-based food as meat substitutes, such as an insect-based burger, reinforces consumers to compare them with meat products, expecting them to taste similar (Derkzen et al., 2011; Hoek et al, 2011). Tasting an insect-based product that is supposed to correspond to a meat alternative can result in an unsatisfactory sensory experience. Consequently, after the initial negative tasting experience, most of the “Potential adopters” reject the innovation.

The model base run demonstrated that diffusion of radical innovations, such as insect-based foods, takes a long time, as many years have to pass before there is a high rise in the number of “Adopters”. The diffusion process of insect-based foods among the Dutch population started only recently and many years may pass before all Dutch consumers become aware of such foods, under the assumption that insect-based food will continue being available and promoted.

4.2. Analysis of scenarios

We proposed several simple scenarios (Table 4.3) to study the influence of change in various model variables on model behaviour, bearing in mind that the variables we changed can be influenced in real life, for example when developing launch strategies. Each of the scenarios targets only one or two model variables, to establish a clear connection between the parameter change and the emergent model behaviour.

In scenario 1, we analysed the effect of an increase of internal (WoM) and external influence (promotion) on adoption rate and on the overall adoption outcome, compared to the model base run. Figure 4.4 contains the results of the analysis. Due to the low sensitivity of the variable "fraction of potential tasters from promotional activities" (see Supplementary material 3, Figure S3.1), we only displayed the effect of doubling the variable "strength of the word-of-mouth" (internal influence, s1.1), and of both increased promotional activities and WoM (s1.2). Increased WoM (s1.1) raises the rate with which the stock of "Potential adopters" depletes, compared to the base run, which leads to a faster tasting rate, and also to a faster adoption rate (see the increase in the stock of "Adopters"). However, both adoption outcomes are similarly low in both s1.1 and s1.2. The problem lies partially in the low sensory quality of insect-based burgers and in the high barriers towards adopting insect-based food ("average taste expectation" and "average appropriateness"), which are the direct cause of "likelihood to adopt". Van Huis et al. (2013) stated that such barriers are deeply embedded and are not easy to change, especially with people highly sensitive to animal reminder disgust (Hamerman, 2016). "Animal-reminder disgust is based on reminding people of their own animal nature" and mortality, e.g., injuries to the body or death (Hamerman, 2016, pp. 320; Olatunji et al., 2008). Furthermore, when both the internal and the external influence are increased (s1.2), there is almost no change in adoption rate, compared to scenario s1.1. Promotional activities may have a somewhat positive impact on willingness to try unusual foods in future situations (van Huis et al., 2013; Looy and Wood, 2006). However, their long-term influence is weak, as such promotion cannot reach many people (Hamerman, 2016). Nevertheless, promotion is a relevant ingredient towards wider familiarity, and consequently, consumption of insects (Shelomi, 2015). It provides people who "seed" the population and initiate WoM (Sterman, 2004), but it should not be the only strategy when the main goal is adoption of insect-based food

Table 4.3. *Description of the three different scenarios as simulation experiments*

Scenario	Description	Value or formula (unit) of the changed variable
Scenario 1 (s1) Internal and external influence	Scenario 1 tests the effect of increase in internal and external influence, compared to the base run. In the first case (s1.1), only the value of the variable "strength of the word-of-mouth" increases for 10% from the year 2015. In the second case (s1.2) both "strength of the word-of-mouth" and "fraction of potential tasters from promotional activities" are increased (10% and 100% respectively) from the year 2015 (when insect-based burgers became available on the Dutch market).	**(s1.1)** "strength of the word-of-mouth" = 0.151 + STEP (0.151*1.1, 2015) (1/Year) **(s1.2)** "fraction of potential tasters from promotional activities" = 0.0036 + STEP (0.0036*2, 2015) (1/Year); "strength of the word-of-mouth" = 0.151 + STEP (0.151*1.1, 2015) (1/Year)
Scenario 2 (s2) Sensory quality improved	Scenario 2 tests the effect of gradual (s2.1) and immediate (s2.2) increase in sensory quality of insect-based burgers, compared to the base run. In the first case (s2.1), the value of the "average sensory quality of insect-based burger" variable increases linearly from the year 2017 until 2048. In the second case (s2.2), it increases immediately.	"average sensory quality of insect-based burger" = **(s2.1)** linear growth from 0.54 (Dmnl) in year 2017 to 0.8 (Dmnl) in year 2048 **(s2.2)** 0.8 (Dmnl) from the year 2017
Scenario 3 (s3) Likelihood to adopt increased	In scenario 3, the effect of changed "likelihood to adopt insect-based food" variable on adoption rate is tested. Instead of only comparing it to the base run, we employed what has been learned in previous scenario. We increased the variable "likelihood to adopt insect-based food" (s3.1) and compared it to the base run, and to the model run when both likelihood to adopt and sensory quality are increased (s3.2)	**(s3.1)** "likelihood to adopt" = WITH LOOKUP (barrier towards adopting, ([(0,0) - (1,1)], (0,1), (0.55,0.19), (1,0)) (Dmnl) **(s3.2)** variables changed according to S3.1 and S2.2

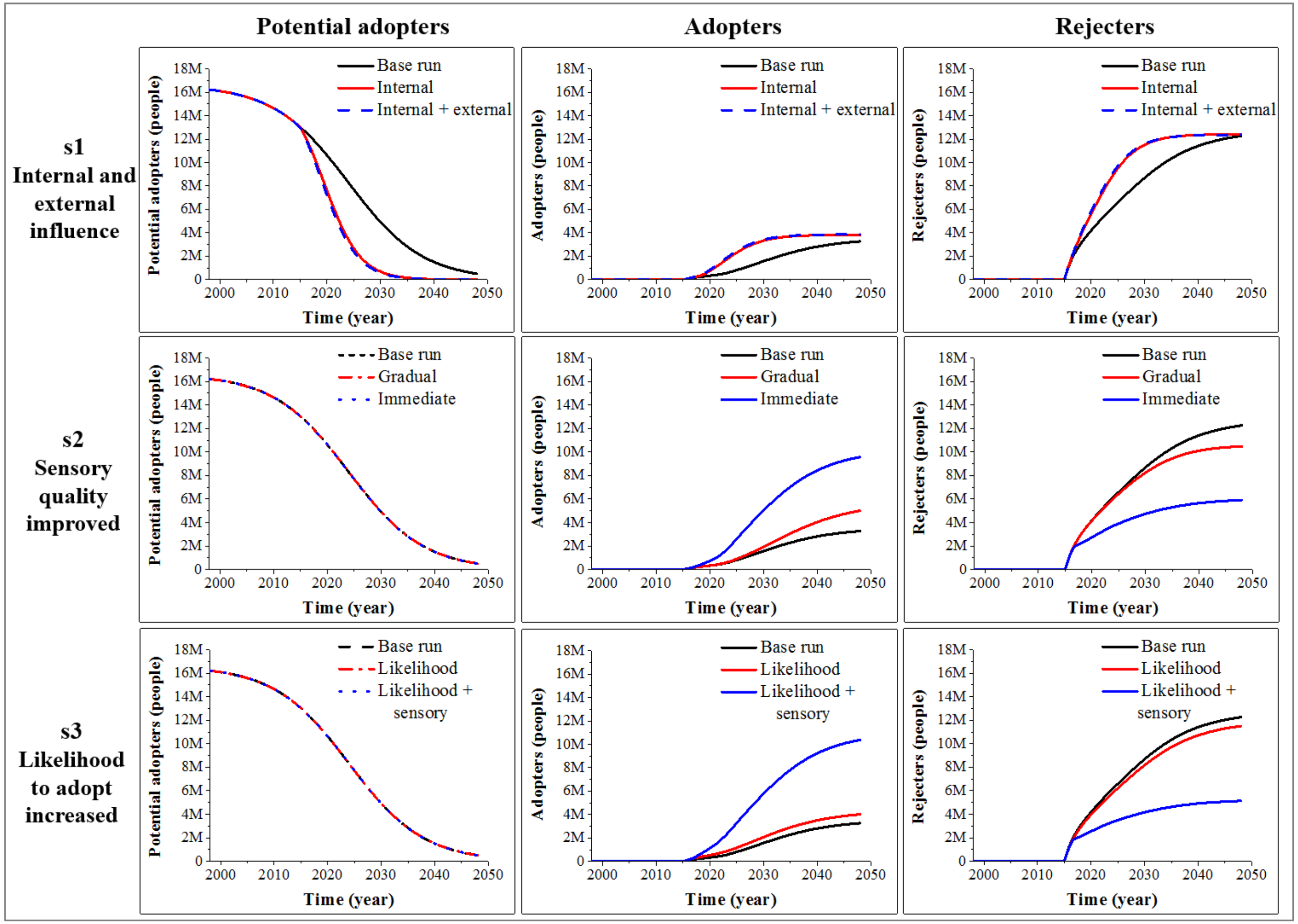


Figure 4.4. *Behaviour of "Potential adopters", "Adopters", and "Rejecters" stocks for 3 different scenarios (scenario 1 (s1): increase in internal and external influence; scenario 2 (s2): increase in sensory quality; scenario 3 (s3): increase in likelihood to adopt.*

In scenario 2, we studied the effect of increased sensory quality on model behaviour (s2.1 and s2.2), compared to the base run behaviour. Firstly (s2.1), we assumed that the improvement in sensory quality of burgers will be gradual, and the value of the variable "average sensory quality of insect-based burger" will increase linearly from the year 2017 until 2048. In the second case (s2.2), we wanted to explore adoption of a very tasty insect-based burger already from the year 2017, which is a product that has not yet been reported in scientific literature (e.g., Tan et al., 2017; Caparros Megido et al., 2016; Schouteten, 2016). Contrary to the first scenario, there is an increase in the overall adoption in both cases. Gradual improvement in the sensory quality of insect-based burgers could lead to a faster adoption rate and increased overall adoption. This effect is even more emphasized in the case of immediate improvement in sensory quality, which could lead to an even greater overall adoption among Dutch population after 50 years of diffusion. However, due to, once again, barriers towards adopting, there could still be a high number of rejecters. High sensory liking is not sufficient for incorporating an insect-based product into regular consumption (Tan et al., 2017). Scenario 2 indicates that improvement in sensory quality of insect-based products is an urgent need. The longer people are exposed to products that are not tasty, the more cumulative rejecters there are. Assumingly, some rejecters will decide never to taste insect-based products again, even if the products become tasty in the future. Consequently, making available insect-based food that is not yet of high sensory quality is a strategical decision that can hinder broader consumption of such food in the long run.

Finally, in scenario 3, we analysed how a change of the variable "likelihood to adopt insect-based food" affected model behaviour. In edible insects literature, the likelihood to adopt has been assessed through willingness to eat (e.g., Vanhonacker et al., 2013) or readiness to adopt (e.g., Verbeke, 2015), with substantial differences in reported quantitative values. Here (s3.1), we chose one of the higher reported values (e.g., Verbeke, 2015) to compare simulation results to the base run, but also to the situation of an immediate increase in sensory quality of insect-based burgers in s3.2. The value of the "likelihood to adopt insect-based food" variable in s3.1 and s.3.2 is 1.6 times bigger than in the base run. Figure 4.4 shows that changing the value of "likelihood to adopt" in s3.1 can have an effect on increasing the adoption outcome, however, much less than 1.6 times. The "barrier towards adopting", resulting from unfamiliarity and expectations of negative taste, and negative appropriateness, directly affects the likelihood to adopt (Baker et al., 2016; Tan et al., 2016). To observe a substantial change in adoption, there is a need for combining an increase in adoption likelihood with an immediate increase in sensory quality of the product, as in s3.2. Scenario 3 shows the importance past experiences with insect-based food have on adoption of such food (Tan et al., 2015; Loo and Sellbach, 2013). Beliefs acquired from past experiences do not change fast. However, introducing immediate positive incentives, such as high sensory quality, can move adoption in a beneficial direction.

5. Discussion

In this paper, we aimed at extending an existing SD Bass diffusion model to develop and simulate adoption of a radical new food product, i.e., an insect-based burger. Figure 4.5 graphically demonstrates the extended boundary of our model, compared to the original SD Bass diffusion model (e.g., Sterman, 2004). The extended SD Bass diffusion model offered a basis to explore insect-based food diffusion as a complex dynamic problem, by identifying cause-effect relationships among major variables, and by examining the outcome of diffusion over a longer time horizon (Tan et al., 2016; Barlas, 2009; Sterman, 2004; Ford, 1999; Richardson and Pugh III, 1981). Instead of focusing on ‘detail complexity’ of food choice, i.e., the quantity of system components, we aimed at studying ‘dynamic complexity’, i.e., the behaviour over time that the model produces (Sterman, 2004). By grounding the literature review in DoI and the Bass diffusion SD model, we were able to select variables from existing literature, which are relevant to represent consumer adoption over time as a dynamic complex problem, and to present them in the form of a stock-and-flow diagram.

The model facilitated exploring the extent to which current literature on edible insects supports studying consumer adoption over time. We were able to identify mechanisms that require further investigation, and the data that is needed to increase the understanding of insect-based food adoption. For example, effects such as negative word-of-mouth, and adoption of insect-based burgers by people who initially reject them, were not included in the model, while they were also omitted in the original Bass diffusion model (Sterman, 2004). Moreover, they have not been studied in the literature on edible insects. Furthermore, the effect of price has rarely been researched in insect-based food literature (House, 2016), and we could not fully include it in the model in Figure 4.2 due to a lack of appropriate data and clarity of mechanisms. These identified knowledge gaps are potential future consumer research opportunities.

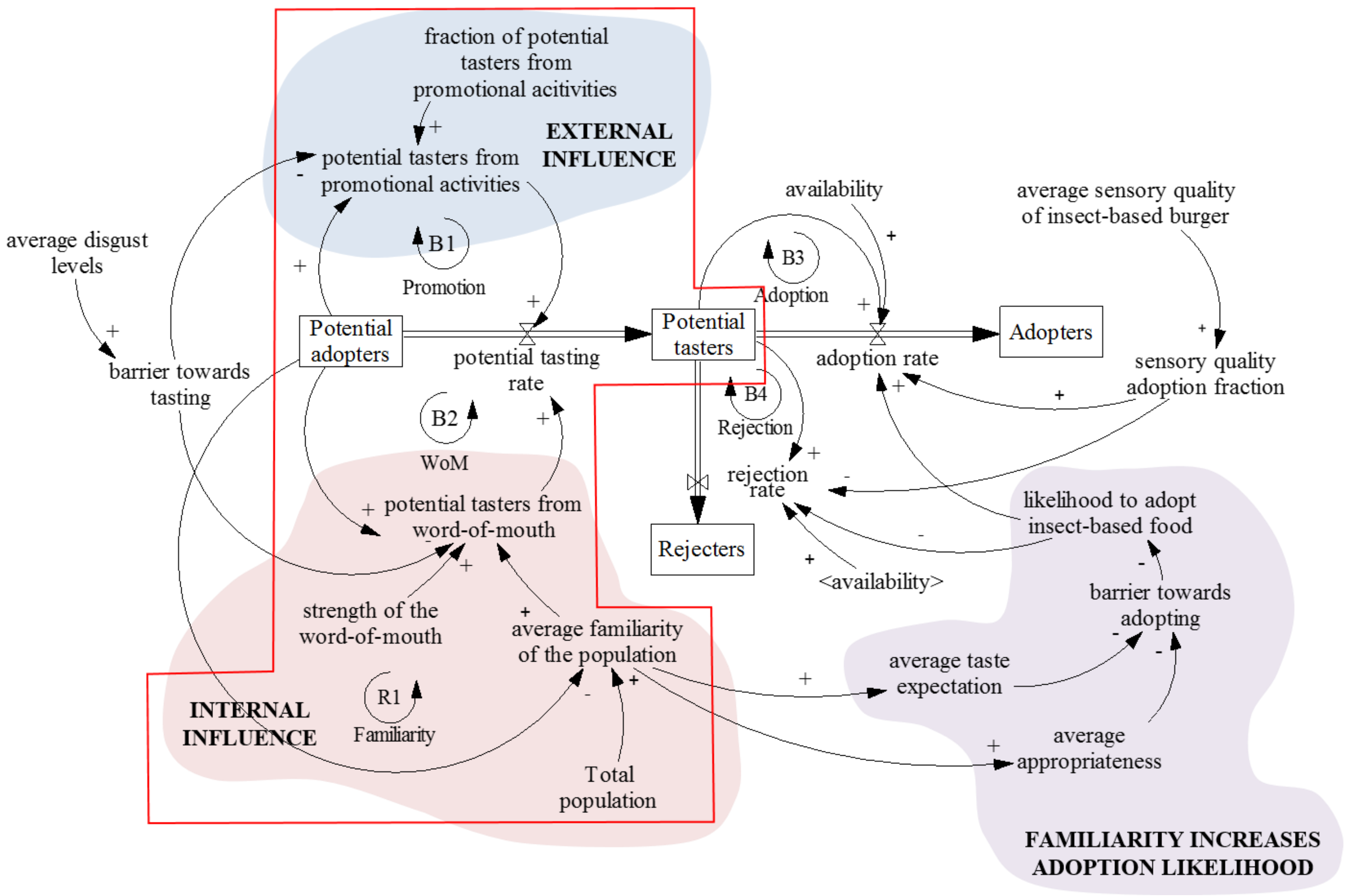


Figure 4.5. *Boundary of the adapted SD Bass diffusion model (the whole stock and flow diagram) and the original SD Bass diffusion model (the part of the stock and flow diagram inside the red lines).*

Confining the model boundary to DoI and the Bass diffusion SD model imposed certain trade-offs that affected the level of detail with which consumers are presented in the model. Consumers' decisions are a result of complex individual psychological processes and SD does not fully allow inclusion of variations among individual consumers in a social system. SD models belong to a group of aggregate models where consumers are studied as a perfectly mixed collection of individuals with an aggregated behaviour, instead of representing individual behavioural characteristics of consumers (Yücel and van Daalen, 2011; Goldenberg and Shapira, 2009; Sterman, 2004). Separating consumers into different groups based on socio-demographic characteristics could be one of the future model improvements, after appropriate data collection. If one aims at modeling the micro-level of consumer behaviour and at capturing individual psychological consumer characteristics, another computer modelling method would be more appropriate, for example, agent-based modelling (Behdani, 2012; Sterman, 2004).

The system dynamics approach has rarely been used on topics related to processed food products. One example is the model developed by Zhao and Zhong (2015), who explored the effect of carbon labelling of milk on the occurrence of ordinary and loyal customers of such products. Their model focused on extrinsic product characteristics (i.e., the characteristics communicated on the packaging) affecting food choice and it involves variables related to environmental aspects of food product attributes. The SD model presented in this paper is the first example of employing the Bass diffusion model to study adoption of radical foods. In our model, based on existing literature on insect-based foods, the focus is on aspects of consumer food choice such as sensory quality, disgust and food appropriateness, which can be altered by adjusting intrinsic product characteristics (e.g., taste, texture). For example, by using grinded, instead of whole insects, consumers experience less disgust, which can have a positive impact on sensory quality and food appropriateness perception (Tan et al., 2015). To estimate future trends in adoption of conventional and radical foods, both extrinsic and intrinsic product characteristics, together with other marketing mix aspects, should be represented by model variables. However, this should also be supported by an appropriate data collection, which is currently a limiting factor in the case of insect-based burgers. Data scarcity in the edible insects field has been recognized earlier by a few authors (House, 2016; Vanhonacker, 2013), and it could be a sign of a limited view to solving the insect-based food adoption problem (Sterman, 2004).

The current model was developed to showcase the SD modeling and simulation approach as an opportunity towards broader utilization of modelling in studying complex dynamic problems in food science and consumer research. The model is suitable for understanding the extent to which current practices, under the proposed framework, affect the rate of insect-based food adoption. However, it is not suitable for understanding if people will buy a product in a market environment. Instead of predicting the exact number of adopters of edible insects, it serves as an example of a method to develop “white box” models in consumer research. Commonly used empirical modeling approaches do not consider underlying mechanisms, and seek simplified relationships to correlate variables, while “white box” models aim at representing those mechanisms (Saguy, 2016). Similar consumer models could have a standard use in new food product development, once enriched with data that would more closely mimic the marketplace situation. Consumers are changing (Grunert, 2015), and food companies need to be able to develop optimal product strategies fast. Using SD models prior to launching new products could help product managers in their decision-making, by testing the consequences of their actions on consumer product adoption over time. SD models could also serve the purpose of steering future marketing and consumer research, after discovering model variables that substantially affect model behaviour. Moreover, similar SD models could be used as learning tools, by giving managers a chance to learn from experimenting with the model.

The initiative for consumption of edible insects in Western countries comes from a need to reduce livestock protein consumption to decrease negative environmental impact of the livestock sector (Gerber et al., 2013). According to Kim et al. (2019), foods of animal origin contribute to 18% of calorie and 25% of protein intake worldwide. Moreover, due to the growth of the population, an increase of 57% in global demand for meat between 2005 and 2050 was projected (Kim et al., 2019). Insects are a promising source of nutrients for humans and their production results in lower greenhouse gas emissions (Dobermann et al., 2017; Oonincx et al., 2010). Therefore, the topic of insect-based food consumption is not only relevant for companies that develop such products, but also for governments. The SD model in this study suggested a low adoption of an insect-based burger in the Netherlands under currently reported practices, which can imply that similar products might also have a low adoption. There is a need to evaluate which government policies might positively impact future consumption of edible insects and how. The SD approach can be beneficial in that respect and similar models could facilitate uncovering potentially successful governmental policies, which would reinforce a widespread consumption of more sustainable sources of protein such as insects. However, existing literature on edible insects does not address the role of governments in supporting the adoption of edible insects, and more research is needed to uncover which policies could be implemented in the future. In the past, the SD approach has been employed to study topics of public relevance related to food consumption, such as obesity (e.g., Fallah-Fini et al., 2014). In the future, SD models could also be used to examine which public initiatives could potentially lead towards more sustainable food consumption.

6. Conclusions

In this study, we developed an extended SD model of insect-based food adoption in the Netherlands, based on current literature on edible insects. This is the first application of the SD approach to study the complex problem of adoption of radical new foods from a dynamic perspective, and it aimed at showcasing an example of developing a “white box” model for use in food science and consumer research.

The extended SD Bass diffusion model allowed representation of current findings in literature on edible insects in the form of an aggregate stock-and-flow model, which offered a means of experimenting with various adoption strategy scenarios. The base run demonstrated that the diffusion process in this case has been slow. The main learning outcome was that the internal model structure we developed can explain the adoption process of insect-based food. The main mechanism that can strongly affect diffusion of such food is word-of-mouth. Therefore, the advice for the future would be that attention needs to be given to triggering consumers to communicate their positive experiences with tasting insect-based food to people who have not tasted such food. Moreover, based on current literature on edible insects, we could build an SD model having a narrow boundary. More concretely, past studies on insect-based food mainly explored factors related to consumer psychology of choosing insect-based food, which were the basis for our model. However, multiple other stakeholders influence the process of food adoption, such as food companies competing on the market, and governments setting regulations. This could indicate that, currently, the problem of insect-based food adoption is tackled from a narrow perspective, which could be an obstacle towards developing successful strategies for adoption of insect-based food.

Furthermore, SD was beneficial in uncovering knowledge gaps that can guide future research. Based on our findings, we suggest that future consumer research on insect-based food should be performed by separating research on willingness to taste food for the first time from research on willingness to adopt certain food, since they are guided by different mechanisms.

Furthermore, mechanisms related to positive and negative word-of-mouth, and adoption of insect-based burgers by people who initially reject them should be addressed. Also, the influence of factors like availability, strength of the word-of-mouth, and promotional activities on adoption should be addressed by collecting relevant data. Furthermore, longitudinal research, in which consumers would be observed throughout longer time, should be established, to provide data for the future development of similar models. Further improvement of this SD insect-based food adoption model could be made by collecting data from other sources (e.g., sales data from retailers or food companies) and by expanding the scope of the model (e.g., to include marketing mix elements, influence of government incentives, and technological development), and by collecting sales data of existing insect-based food to assess its forecasting power. Lastly, future research could move towards employing other simulation modelling methods that can be used for dynamic complex problems, or by combining them with SD. For example, in agent-based models, consumers are represented as individual agents, instead of in an aggregated way. Such a model can stand alone or be an addition to an SD model.

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Chapter 5

Supporting team collaboration in product life cycle management in a food processing company: A participatory system dynamics modelling approach

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Abstract

Product life cycle (PLC) analysis aims at studying patterns of product sales over time and the reasons behind those patterns. Such analysis can be challenging, especially in the food processing industry, because of the interconnected effect of technical product characteristics, marketing mix elements, and the influence of environment (e.g., competition, consumers). Therefore, PLC analysis of food products calls for cross-functional collaboration of various company functions, such as marketing, R&D, sales, etc. However, employees from different functions have different backgrounds and perceptions about the system structure and origin of patterns of product sales in the PLC, which constrains mutual understanding and hampers decision-making. The group model building (GMB) approach can be an effective participatory method to support teams with multiple stakeholders in solving complex dynamic problems, such as PLC analysis of product sales. This study uses the GMB approach and presents a system dynamics model, which supported cross-functional collaboration in understanding potential causes of stagnating product sales in the PLC in a food processing company. The GMB method was applied to structure and understand the causal conditions that underlay stagnating sales of a healthy snack product. Through multiple GMB sessions with the company team, a system dynamics model was developed and a number of strategies were analysed. The GMB process of developing the model has proven useful in studying possible interventions for stagnating product sales of the product in case Moreover, GMB was successful in improving communication among the GMB participants, and creating shared vision about the problem.

1. Introduction

One of the main goals of food companies is a continuous and fast development and launch of new food products. Products that succeed usually assure a big portion of company's profit, while product failures represent substantial financial loss (Grunert and van Trijp, 2014; Ogawa and Piller, 2006). To enhance sustainable product success, firms need to study how they perform new product development (NPD) and how they execute post-launch activities during the product life cycle (PLC). While numerous studies investigated NPD activities and gave recommendations for improving product success, a limited number of studies focused on PLC. For example, Kalluri and Kodali (2014), in their review, identified 1127 scientific articles on NPD written in a 12-year period, whereas Cao and Folan (2008) only found 115 scientific articles on PLC in a 60-year period. Past PLC research investigated topics like advertising, pricing, competition, and demand modelling, and mainly focused on consumer durables (e.g., Chan and Mills, 2015; Desmarchelier et al., 2017; Makinen and Desavelle, 2013; Melser and Syed, 2016; Wu et al., 2017). However, to the best of the authors' knowledge, no studies in the context of assuring product success in PLC in food industry have been done.

PLC is commonly described as a change in product sales over time throughout the four phases, i.e., introduction, growth, maturity, and decline, wherein multiple activities take place (Plewa, 2016). In the introduction phase, companies perform activities aimed at promoting the product to improve initial product familiarity among consumers and to increase sales (Weng and Huang, 2018). In the growth phase, product sales grow rapidly and in order to sustain this rapid growth firms can work on improving product quality, adapting advertising, or lowering prices. In the maturity phase, when the sales start stagnating, firms can enter new segments, attract competitors' consumers, or optimize production to lower costs and increase profit. In the decline phase, when product sales decline, firms can further increase product quality, or ultimately, withdraw the product from the market (Weng and Huang, 2018; Kotler, 2003). Product sales behaviour in PLC is a typical complex dynamic problem. It involves making decisions about a multitude of formerly mentioned activities, which in turn will affect how sales behaviour evolves over time (e.g., Warren, 2008).

In different PLC phases, teams consisting of people with different functions (e.g., marketing, R&D, sales, production, and quality control) make various decisions and perform different activities to realise satisfactory product sales (Kotler, 2003). Researchers identified cross-functional team collaboration as one of the critical factors for successful development of products (Barczak et al., 2009; Edmondson and Nembhard, 2009). However, collaboration in cross-functional teams is very challenging (Jacobsen et al., 2014). People with different functions have different perspectives and sometimes have conflicting interests. This can cause less mutual understanding and difficulty in decision-making (Darawong, 2018; Sethi, 2001). Although people in a team initially tend to establish a consensus on product goals, they commonly perform actual activities in isolation from each other (Jacobsen et al., 2014). To overcome these challenges, teams are encouraged to meet frequently face-to-face (Jacobsen et al., 2014; Vennix, 1996). However, team meetings are not always properly structured, their purpose is not clear, participation of attendees is not always of high quality, or one person dominates the conversation (Axtell, 2018). These common challenges in team collaboration could hinder companies in developing strategies that would insure successful product performance during PLC.

To support teams or groups of people in making informed collective decisions in organizations, the operations research and group decision and negotiation fields recommend the use of formal procedures and systematic approaches (Luoma, 2016; Franco and Montibeller, 2010; Kilgour and Eden, 2010). Group model building (GMB) is one of the group decision and negotiation approaches particularly aimed at structuring complex dynamic problems, such as product sales in PLC, with a group of stakeholders (Ackermann et al., 2014; Richardson and Andersen, 2010; Andersen and Richardson, 1997). GMB aims at uncovering elements of a complex system and their causal interrelations (Vennix, 1996). An outcome of GMB is a system dynamics (SD) model to investigate strategies for tackling the problems (Richardson and Andersen, 2010; Vennix, 1996). In the case of food product sales in PLC, an SD model would contain elements that represent PLC activities and factors relevant in understanding how the product sales evolve over time. It could be used to make informed future decisions in cross-functional teams. Group model building has been applied to various complex dynamic problems in multiple areas, such as policymaking, strategy development and implementation (e.g., Lane et al., 2019; Rouwette et al., 2016; Otto and Struben, 2004). Scott et al. (2016) reviewed applications of GMB in team decision making and almost all the studies provided evidence of the usefulness of GMB in better understanding of complex dynamic problems in group decision-making. The usefulness of GMB arises from participants' improved interdisciplinary learning, from building a consensus and a shared vision of the problem, and from developing mutual goals to solve the problem (Scott et al., 2016; Rouwette et al., 2002). Although the use of GMB approach in the food industry context has not been reported, it is expected that this approach could facilitate the overcoming of typical challenges in multidisciplinary team collaboration in assuring food product success in PLC. In this study, we used the GMB approach to support cross-functional team collaboration in understanding a problem related to food product sales in the PLC. The GMB approach was applied in a case of stagnating sales of a healthy fruit snack. Moreover, we investigated the usefulness of this approach in supporting team collaboration and decision support in a multi-stakeholder situation. The paper is structured as follows. Firstly, the particular GMB process in this study is described, after which the outcomes of each GMB session and the post-test survey are presented. Finally, we discussed the potential causes of stagnating sales of the healthy food snack, and the usefulness of the GMB approach in supporting cross-functional team collaboration.

2. Method

2.1. Stages of the GMB process

In this study, the GMB process consists of the following stages: model conceptualization, model formulation, model testing, and presentation of results (Figure 5.1), following the principles of Vennix (1996) and Albin (1997). GMB sessions were designed with the help of scripts. Scripts are “fairly sophisticated pieces of small group process”, which describe small-group activities (Andersen and Richardson, 1997, pg. 107). Each script generates products, which are relevant for building an SD model and for generating recommendations for a problem being studied. ScriptsMap framework was used to design GMB sessions (Ackermann et al., 2011). Table 5.1 shows the list of scripts that were used to structure the GMB sessions.

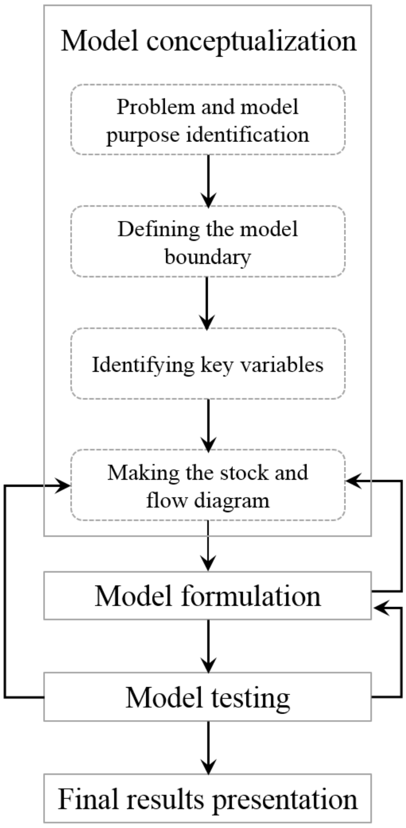

Figure 5.1. *Stages of the group model building (GMB) process in this study, based on Vennix (1996) and Albin (1997). The arrows represent the progression through different GMB stages in this study.*

Table 5.1. *Activities and scripts used in different stages of the GMB process*

GMB stage	Script name or activity	Purpose	Product	Source
Model conceptualization				
Problem definition and model purpose identification	No specific script used Group meeting with participants and individual interviews	To identify a relevant dynamic problem and to define the purpose of the SD model. To increase familiarity with the participants and assess their connection to the identified problem.	Problem definition and model purpose	Vennix (1996)
Defining the model boundary	Model boundary elicitation	To list stakeholders relevant for the problem and strategies that the participants have tried in the past or would want to employ in the future.	Key stakeholders and key strategies	Hosseinichimeh et al. (2017), Eden and Ackermann (1998)
	Dots	To select the stakeholders and strategies that are the most important for the participants.		Hovmand et al., (2013)*
Identifying key variables	Graphs over time	To elicit model variables and their reference modes (graphs of behaviour over time).	Key variables and their reference modes	Hovmand et al., (2013)*
	Dots	To select the variables that are the most important for the participants.		Hovmand et al., (2013)*
Making the stock and flow diagram	Concept model	To introduce the process and the symbolism of building a system dynamics model.	Stock and flow diagram	Hovmand et al., (2013)*
	Causal mapping with the seed structure	To quickly elicit causal structures in a stock and flow diagram.		Hovmand et al., (2013)*
	Transferring group ownership from one image to another	To move from a structure developed through group discussions in a GMB session to a cleaner version created by the modeller after the GMB session.		Hovmand et al., (2013)*
Model formulation	Parameter booklet	To collect numerical data for model parameters.	SD model that can be simulated	Hosseinichimeh et al. (2017)
	Nonlinear functions elicitation	To estimate table/look up functions for model variables.		Ford and Sterman (1998)
Model testing	What-if analysis	To test how large changes in selected model variables affect the model behaviour. If the existing model behaviour does not correspond to participants' expectations, the information that participants provide about the causes of the expected model behaviour are used to further improve the SD model.	Improved SD model	Rizzi (2018)
Final results presentation	No specific script used Group meeting with participants	To present interesting solutions to the problem, in the form of model runs.	Simulated scenarios	-

*Detailed description of the procedure of executing the scripts is available from Scriptapedia: https://en.wikibooks.org/wiki/Scriptapedia

2.2. GMB process in this study

2.1.1. The participating company

The company participating in the GMB project is a young small food company situated in Europe. The company produces fruit-based processed products. In total, six company participants attended the GMB sessions and two modelling team members were present (see Table 5.2). Table 5.3 shows the agenda of the GMB sessions.

Table 5.2. *Profiles of participants in the GMB sessions and their attendance*

Participant profile	Attendance
Company participants	
Company director	Initial group meeting, individual interview, 4 GMB sessions
Marketing manager	Initial group meeting, individual interview, 4 GMB sessions
Sales representative	Initial group meeting, individual interview, 4 GMB sessions
Sales representative	Initial group meeting, individual interview, 4 GMB sessions
Quality assurance manager	Individual interview, 2 GMB sessions
Production manager	2 GMB sessions
Modelling team	
University researcher – facilitator and modeller	Initial group meeting, individual interviews, 4 GMB sessions
Researcher in private sector – modeller and helper	3 GMB sessions

Table 5.3. *The public agenda of the group model building (GMB) sessions*

No.	GMB session 1	GMB session 2	GMB session 3	GMB session 4
1	Participants introduction	Review of the 1st session	Review of the 1st and the 2nd session	Review of the past sessions
2	Problem introduction	Model structure elicitation	Presentation of the system dynamics model behaviour	Presentation of simulated scenarios
3	Hopes and fears	Model review	What-if exercise	Exercises – participants use the model interface
4	Key stakeholders elicitation	Next steps and closing	Presentation of the stock and flow diagram on consumer buying behaviour	Closing the session
6	Strategy elicitation		Validation of the stock and flow diagram consumer buying behaviour	Post-test survey
7	Concept model presentation		Nonlinear graphs exercise	
8	Graphs over time exercise		Parameter elicitation exercise	
9	Next steps and closing		Next steps and closing	

2.1.2. Model conceptualization stage

Firstly, a group meeting was organized to define a dynamic problem related to success in PLC, which the company struggled with, and to define the purpose of the model. The group meeting was followed by individual interviews with participants of the GMB sessions to learn about their specific job descriptions and responsibilities regarding the product.

In the **first GMB session**, the model boundary and key variables were elicited. To define the model boundary, participants needed to list stakeholders on pieces of paper. A stakeholder was defined as a person, a group, a department, or an organization that has interest or concern in the defined problem (Eden and Ackermann, 1998). Moreover, the participants needed to list the strategies they have tried in the past or would want to employ in the future to solve the defined problem. In the end, each participant received ten votes, in the form of sticky dots, of which five to distribute among the key stakeholders and five among the key strategies. Lastly, the participants drew graphs of variables related to the problem, which should be captured in the SD model. The graphs needed to show the behaviour of a variable (on the y-axis) over time (on the x-axis). Once again, the participants received five votes to choose the key variables.

The **second GMB session**, which occurred two days after the first one, aimed at making the initial stock and flow diagram (SFD). The main elements of an SFD were explained as stocks, which are accumulations of information or material building up over time, flows, through which an inflow and outflow of material or information occurs, and other variables, which determine the rate of change (Richardson and Pugh, 1981). Prior to building the SFD, participants were introduced to the process and the symbolism of building an SD model (see Supplementary material 4). To start eliciting causal structures in the SFD, the seed structure was used (see Supplementary material 4). The seed structure was built based on the elicited key variables, key stakeholders, and key strategies from the previous session. The overall SFD was built through group discussions, based on the script "Causal mapping with seed structure" (Hovmand et al., 2013) and the guidelines set by Vennix (1996).

2.1.3. Model formulation and testing stages

The first author performed SD model formulation in Vensim software away from GMB participants, based on the guidelines set by Sterman (2004). Some parameters were based on numerical data, which was partially provided by participants (e.g., marketing budget, market share, product sales, maximum product discount, chronological entrance of the product in new points of sales, dates of new product launches, consumer quality complaints). Other parameters were from participants' assumptions and outcomes of the "Parameter booklet" script (Hosseinichimeh et al., 2017). Nonlinear functions were estimated together with participants, according to the protocol set out by Ford and Sterman (1998).

In the **third GMB session** in May 2018, model testing, i.e., the what-if analysis, was performed with participants (e.g., Rizzi, 2018). The behaviour reproduction test was performed by the first author by calibrating the model to the actual data (see Supplementary material 4), together with the dimensional consistency and sensitivity analysis (e.g., Sterman, 2004).

2.1.4. Presenting final results

In the **fourth GMB session** in November 2018, the process ended by presenting various simulated scenarios, which aimed at participants' better understanding of the modelled problem (Vennix, 1996). Moreover, the Vensim model was transferred to the participants (see Supplementary material 4) in the form of an interface, containing parameters that can be changed numerically and graphs of the most relevant stocks.

2.2. Post-test survey to assess the usefulness of the GMB

The usefulness of GMB in supporting cross-functional team collaboration was measured by means of a post-test survey. We used the questionnaire developed by Rouwette (2011), which evaluates participants' improvement in communication, shared vision and extent of insights gained, and commitment to conclusions resulting from participation in the GMB sessions. The questionnaire is in Supplementary material 4.

3. Results

3.1. Conceptualized model

3.1.1. Identified problem related to product success in PLC

In the initial group meeting, the company owner stated that the sales of the company's oldest product have been stagnating (Figure 5.2). Consensus was established to focus on the problem of stagnating sales of the company's oldest product. Therefore, the GMB process aimed at increasing understanding of why the product sales have not been growing as expected.

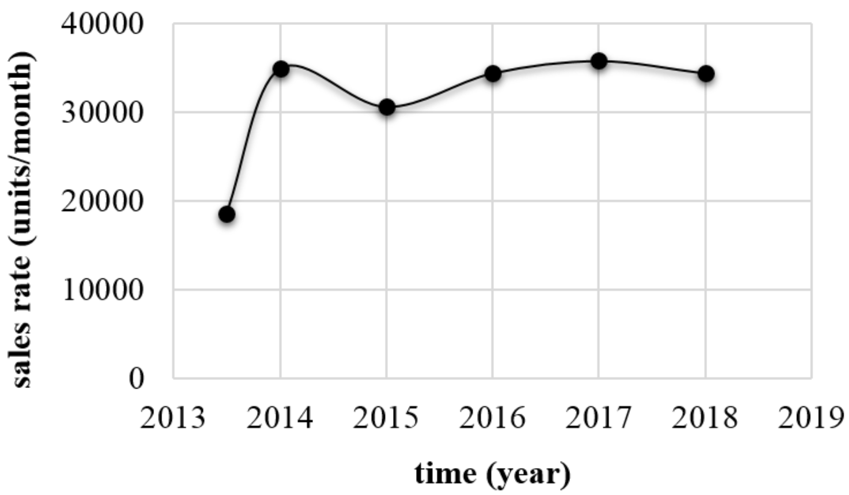

Figure 5.2. *Reference mode of product sales showing average monthly sales of the product from year 2013 to 2018.*

3.1.2. Defined boundary

In the stage of "Defining the model boundary", participants elicited the key stakeholders and strategies. Figure 5.3 shows all the elicited stakeholders. The most voted external stakeholders (outside of the company) were clients (five votes), consumers (four), and suppliers of raw materials (three). Figure 5.4 shows all elicited strategies. The most voted strategies were conducting a large-scale market survey with consumers (five), more communication with consumers (i.e., more marketing activities) (four votes), improvement of sales planning (four votes), easy to open packaging (four votes), improvement of conditions of storing the final product (four votes), and more meetings with internal team (three votes). The modelling team used this information to design the seed structure and determine the major discussion points in the second GMB session.

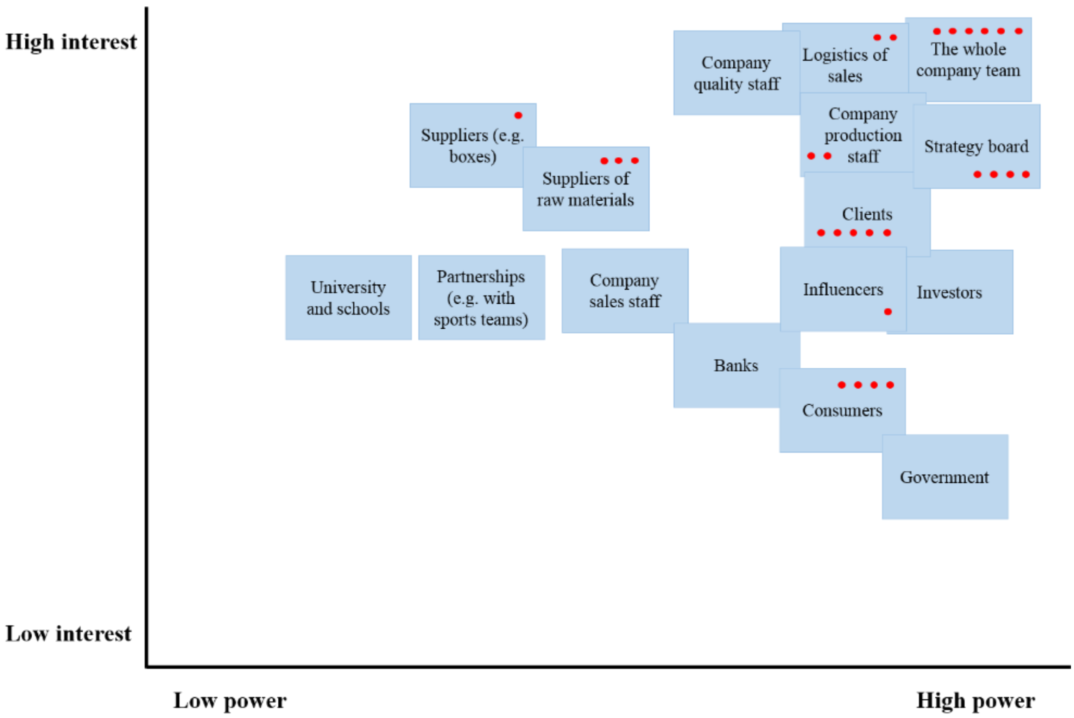

Figure 5.3. *Power-interest grid of stakeholders, elicited with the stakeholder elicitation portion of the "Model boundary elicitation" script. GMB participants positioned stakeholders in the grid based on stakeholder's power to affect the defined problem, and their interest, which implies stakeholders' stake or involvement in the defined problem. Red dots represent participants' votes for the most important stakeholders.*

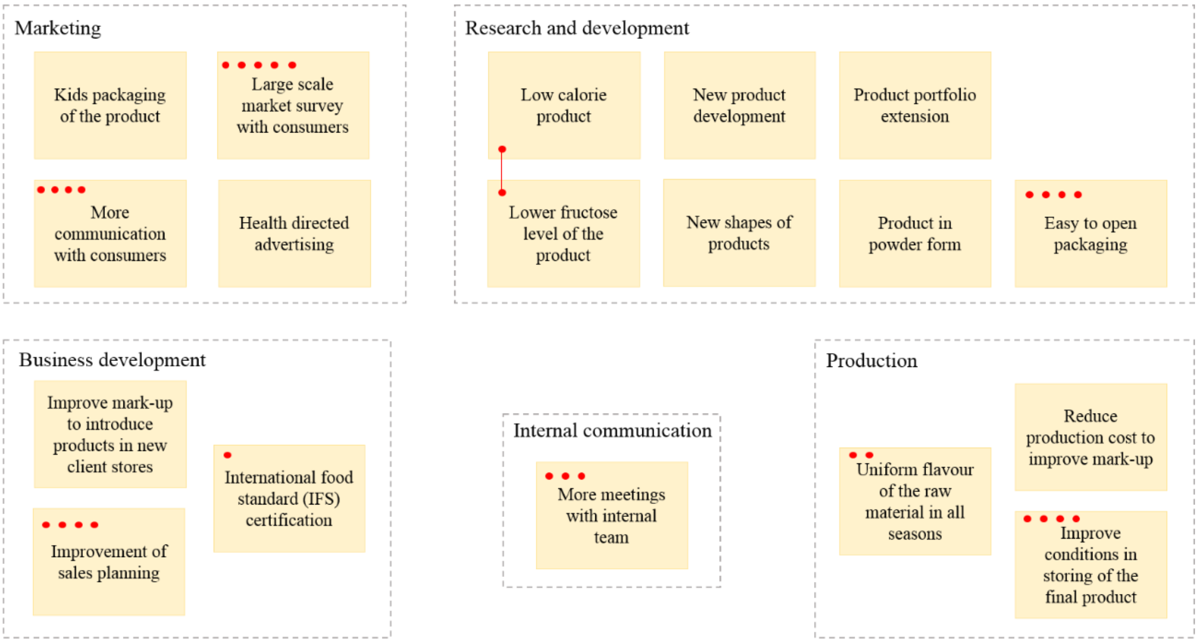

Figure 5.4. *Strategies elicited with the strategy elicitation portion of the "Model boundary elicitation" script, categorized by themes. Red dots represent participants' votes for the most important strategies, in relation to the defined problem. A line between the dots means a participant gave one vote to two strategies.*

3.1.3. Identified key variables

Table 5.4 shows the information elicited in the GMB stage of identifying key variables. The key variables that were elicited include marketing budget, the temperature in the factory, competitors selling healthy products, points of sales, and number of company's products.

Table 5.4. *Key variables elicited with "Graphs over time" script, their description, and the total number of votes each variable received from participants.*

Variable name	Description	Votes
Marketing budget	Represents the amount of money allocated for marketing activities each year.	5
Temperature in the factory	Represents the temperature within the production facilities, which is especially problematic in warm months since the space is not air-conditioned.	5
Competitors selling healthy products	Represents all the competitors on the market whose products fall into the category of healthy food.	4
Points of sales	Represents all the places where the company's product can be bought (e.g., supermarkets, gas stations, vending machines).	4
Number of products	Represents the total number of company's products on the market.	3

3.1.4. The formalized stock and flow diagram (SFD)

Figure 5.5 shows the sector diagram of the conceptualized SFD after the first two GMB sessions, consisting of the stock and flow backbone of the model and the various model sectors affecting the flows. The backbone of the model represents the product's path from the factory (the stock of "packaged product") to the points of sales ("product in the points of sales" stock). The production rate of the packaged product is determined by the "production planning" sector. The client sales rate depends on the stock of the packaged product and the "points of sales" sector of the diagram. Points of sales (e.g., supermarkets, gas stations) represent the number of sales places in which the product is available to the consumers on the market. The sector "product quality" (see Figure 5.5) depicts the occurrence of product defects (e.g., the deficient sensory quality of the product), which can affect "consumer sales rate". This sector was included since in summer months, due to high temperatures and lack of air-conditioning in the factory, the undesirable sensory quality of packaged products occasionally occurs. If this goes unnoticed by the quality assurance department, packages containing a product of undesirable quality may reach the consumers, which may negatively influence their future buying behaviour and companies' future sales rate.

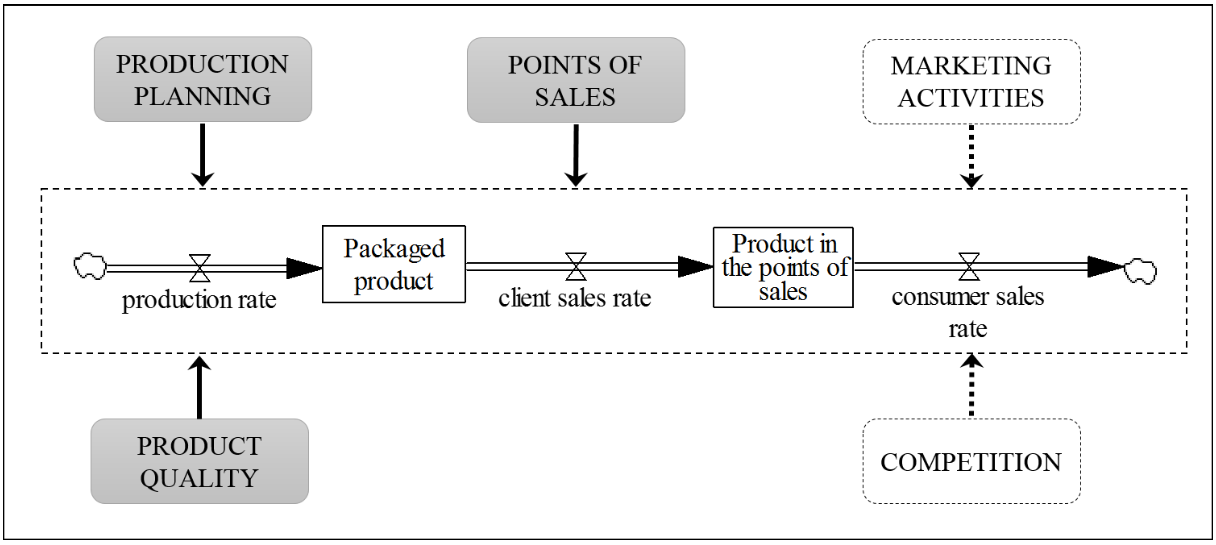

Figure 5.5. *Sector diagram consisting of the stock and flow backbone of the model and various sectors affecting the flow rates. The sector boxes in grey represent the structures that were developed completely after the second meeting, while the white boxes represent the structures that remained unfinished.*

At the end of the second GMB session, the sectors “production planning”, “product quality”, and “points of sales” were represented with a higher level of detail compared to the sectors depicting company’s “marketing activities” and “competition” on the market. After this session, the modelling team formalized and simulated the model structure (Figure 5.5). However, this structure was not able to explain the causes of stagnating product sales. Product quality problems would occur only on rare occasions and in small amounts. Moreover, there was no evident problem in production planning or in entering the points of sales. In the second session, the participants acknowledged that unexplored model sectors (i.e., marketing activities and competition) could have a substantial effect on consumer sales rate. However, their lack of understanding of how those sectors affect the sales rate did not allow for clear mapping of causal structures. Consequently, the modelling team decided to search for theories that would be able to explain the causes of the sales problem due to marketing activities and competition.

For the third GMB session, the facilitating team developed an SFD based on existing theories of consumer buying behaviour, which could potentially capture the company’s impact on product sales through marketing activities, and the effect of competition (e.g., Zhao and Zhong, 2015; Warren, 2008; Schepers et al., 2004). To minimize the negative impact of introducing a literature-based SFD on participants’ model ownership, all elements of the presented SFD were extensively discussed in that GMB session. Firstly, the facilitator addressed each stock and flow and their causal connections to validate if suggested dynamic hypotheses corresponded to the situation with consumers of the healthy food snack. The participants confirmed that their situation corresponds to the suggested SFD model. Moreover, it was discussed which marketing activities affect consumers to move from one stock to another. Figure 5.6 depicts the main part of the SFD of consumer buying behaviour, validated by the GMB participants in the third GMB session.

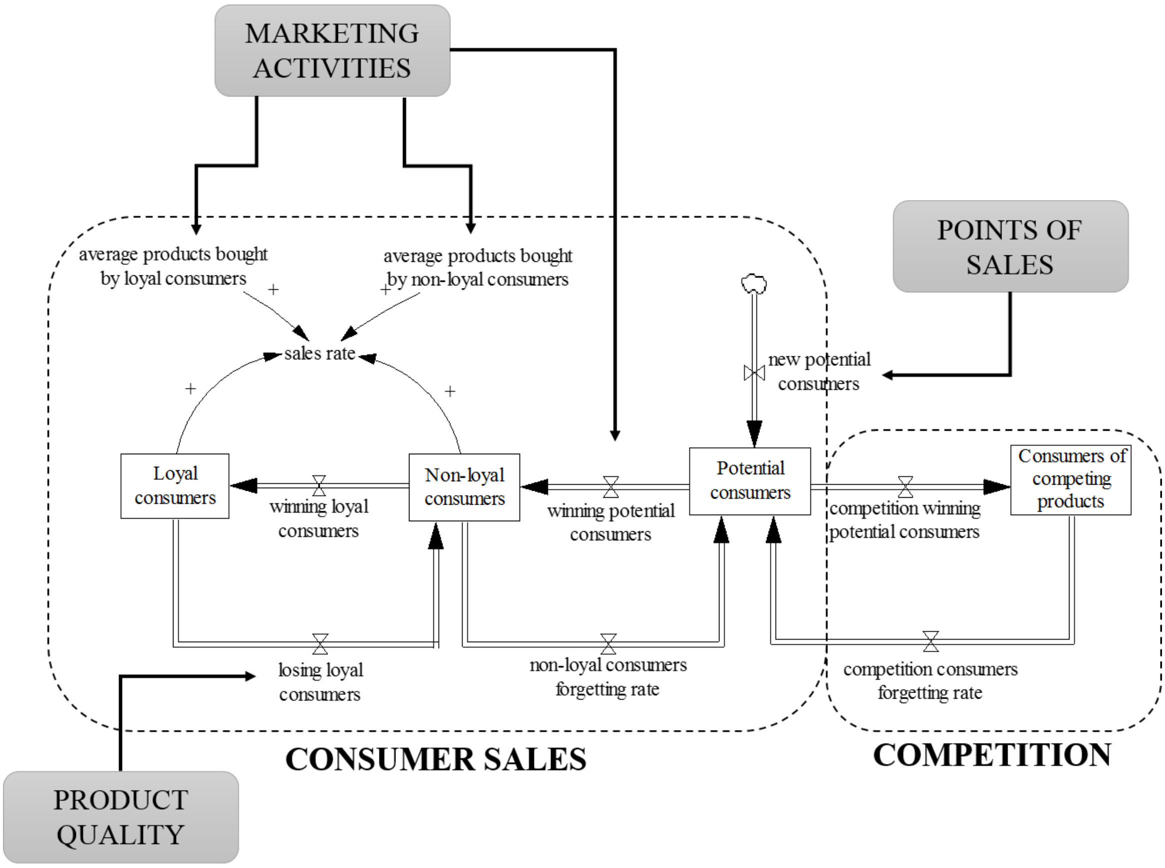

Figure 5.6. *Main parts of the SFD depicting consumer buying behaviour, developed for better understanding of the effect of marketing activities, competition, and product quality on product demand. See Supplementary material 4 for the complete SFD.*

Figure 5.6 shows that there is a stock of “potential consumers” on the market who are interested in the particular type of product that the company is selling. The company acquires “new potential consumers” when the product enters new points of sales. At the same time, there is a continuous competition for “potential consumers” between the company and its competitors. By investing in marketing activities (e.g., discount campaigns, advertising products in supermarket fliers and on social media, sharing product samples, and launching a new product), the company increases the chance of winning “potential consumers”. If the company succeeds in winning potential consumers, those people first become “non-loyal consumers”. With a certain delay, a fraction of “non-loyal consumers” may become “loyal consumer”. “Loyal consumers” monthly buy more units of the product than the “non-loyal consumers”. Figure 5.6 also shows that some “non-loyal consumers” do not become loyal, and after a certain delay they go back to being “potential consumers” until they are influenced by marketing activities again. Moreover, Figure 5.6 reveals that a fraction of “loyal consumers” is lost after a delay of a few months, because they start buying fewer product units. Participants stated that it happens particularly if “loyal consumers” buy a product of lower quality.

3.1.5. Simulated scenarios presented to the GMB participants

In the fourth GMB session, the team presented and discussed simulations of various scenarios of the model structure. The aim was to increase participants’ understanding of the causes of stagnating product sales. The scenarios were chosen based on discussions in the third GMB meeting. They represented the main activities that the company undertakes to move consumers from one stock to another. These scenarios included: 1) product discount campaigns, 2) entrance of a similar new company’s product on the market (i.e., the effect of cannibalization), and 3) product quality issues, to show the effect on average monthly sales (as shown in Figures 5.7-5.9).

Figure 5.7 shows the results of the first scenario related to product discounts. The blue line represents the base run, showing the model behaviour when no product discount has been applied. The company never applies more than 20% discount on the price. Therefore, base run is compared to the model behaviour when a 20% price discount is applied for 3 months (red line), and when a permanent 20% reduction of product price is applied (green line), both starting from January 2019. Based on participants’ assumptions, when there is a 20% product discount, non-loyal and loyal consumers will buy 20% more units of the product than usually. Moreover, when there is a 20% discount, there is also a 5% higher chance of winning potential consumers. Under such conditions, the model shows a temporarily increase in sales rate, followed by sales rate decrease (see Figure 5.7). In the short term, there is a substantial increase in sales during discount months, as a direct result of both existing non-loyal and loyal consumers buying more product units. Moreover, due to the increase in winning potential consumers, there is also an increase in the number of non-loyal and loyal consumers, which further contributes to sales. Nevertheless, in the long term the sales start stagnating. This occurs due to the loss of some of the acquired loyal and non-loyal consumers.

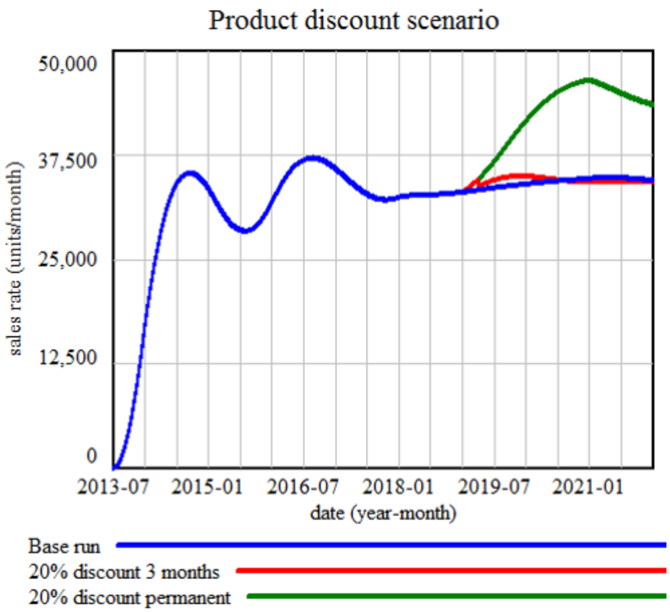

Figure 5.7. *Scenario showing sales rate of a healthy fruit snack when there is a 20% product price discount for 3 months and permanently. Product discount causes loyal and non-loyal consumers to buy 20% more product units, and there is a 5% higher fraction of winning non-loyal consumers.*

Figure 5.8 shows the results of the second scenario when a new similar company's product appears on the market. One of the company's strategies has been to launch line extension products e.g., different flavours of healthy food snacks. When a similar new product appears on the market, the fraction of winning non-loyal consumers of the old product will decrease, because some of the potential consumers will start choosing the new product. With a slight decrease in losing potential consumers (0.4%), the company would experience a modest loss of sales of the old product. This is even more pronounced with a higher loss of potential consumers (2.5%). In this case, the sales of the old product would not recover three years after the new product introduction. While the decrease of 0.4% was based on participants' assumptions from the results of the nonlinear functions script, the 2.5% fraction was estimated based on the average past decrease in the actual product sales when the company had new products entering the market in the past. The 2.5% loss of potential consumers could be an overestimation, since the drop in actual sales could have been caused by various other factors (e.g., competition winning consumers, company entering less points-of-sales, less successful marketing activities). However, also the participant's assumption (0.4%) might be unrealistic since no concrete data exist. Nevertheless, with this scenario the participants could see the sensitivity of the system to new product introductions and the need for careful consideration of product cannibalization effects when launching new products, since this could be one of the causes of the stagnating sales.

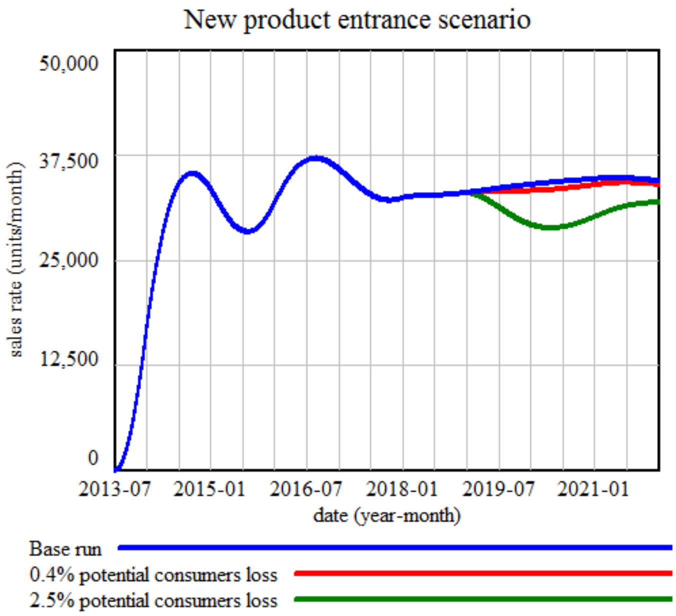

Figure 5.8. *Scenario showing sales rate when a new company's product enters the market, which causes 0.4% and 2.5% loss of potential consumers.*

Figure 5.9 shows the model behaviour when a product with sensory quality issues appears on the market, and when it remains on the market for some time. According to participants, this would mainly affect losing loyal consumers, who would start buying fewer product units. Based on company's consumer complaints data and participants assumptions on the frequency of consumers complaining, it is assumed that 1% of loyal consumers would buy faulty products over two weeks, which would cause them to stop being loyal. Figure 5.9 shows that there is a barely visible difference in product sales rate if quality issues occur for a short period, such as a half month, and affect a small percentage of consumers. However, longer quality related problems (i.e., two months), which would impact a higher percentage of loyal consumers (e.g., 10%) could have a serious impact on product sales (see the green line in Figure 5.9). This will have negative consequences on product sales for many years in the future. Since the company usually does not have serious quality issues for longer periods, the deficient quality was probably not the cause of stagnating product sales. Nevertheless, it is important that the company try to avoiding longer periods of lowered product quality that would affect many people since this can negatively affect product sales.

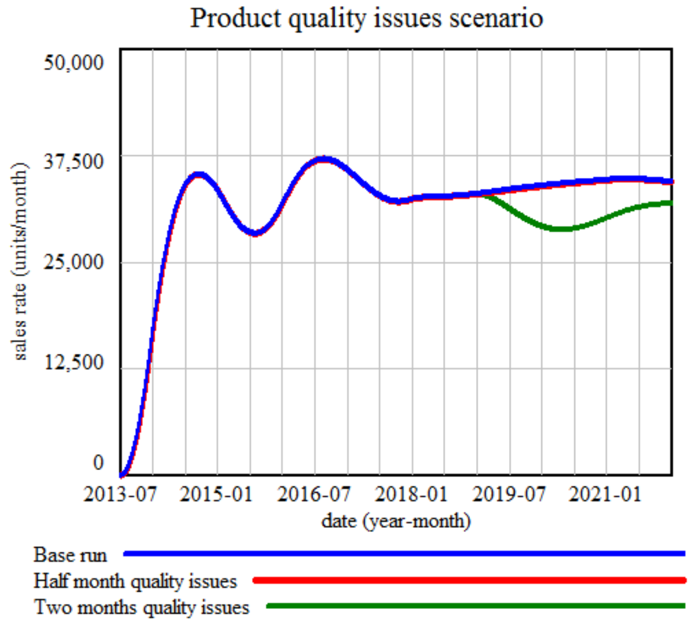

Figure 5.9. *Scenario showing sales rate when there are sensory quality issues with the product for half month and two months, which causes the loss of loyal consumers.*

Lastly, at the end of the fourth GMB session, the participants had an opportunity to perform exercises with the developed model. The modelling team developed an interface, which allowed participants to change the model parameters, and observe the changes in the model behaviour, according to various proposed scenarios. The interface and the exercises are in the Supplementary material 4.

3.2. Results of the post-test survey

Table 5.5 shows the results of the post-test survey. The participants agreed that the GMB approach generated better communication, more insight, and better shared vision of the problem, compared to the usual meetings in which they discussed similar problems. Although the results in Table 5.5 show that commitment was scored the lowest, participants stated that they generally support the conclusions that were drawn during the modelling process, and that they would try to convince others in the company of their importance. Participants stated that the use of the SFD made communication about the problem clearer and it gave them more understanding of the feedback processes that play a role in the problem. Most of the participants appreciated the GMB sessions as they have given them an opportunity for an open and extensive discussion of the problem, and it facilitated teamwork. While some participants felt that the sessions required too much of their time, others stated that they would have liked even more time to discuss the problem to test the model and to perform scenario exercises.

Table 5.5. *Results of the post-test survey*

Compared to usual meetings in which you discussed similar problems, group model building sessions:	**Mean***	**Mode***
generate more insight	4.25	4
result in better communication	4.25	4
generate better shared vision	4.25	4
generate insight more quickly	4	4
generate shared vision more quickly	3.75	4
generate more commitment	3.5	**
generate commitment more quickly	3.25	3

*5 - strongly agree; 4 – agree; 3 – neither agree, nor disagree; 2 – disagree; 1 - strongly disagree

** two participants agree (4), and two participants neither agree, nor disagree (3)

4. Discussion

4.2. A shift in participants' worldview from supply to consumer orientation

The GMB approach in this study was used to increase a company's understanding of their problem of stagnating sales of a healthy fruit snack. In that process, the modelling team and the participants went through the development of two complementary but different SFDs. The GMB participants started with a supply-push view of the problem. This resulted in the model shown in Figure 5.5, which largely focused on production, product quality, and client (points of sales) issues. In this first phase, participants could not say much about how their marketing activities affected their consumers. One sales representative stated that client sales (e.g., supermarkets) are their main concern and that they mostly do not look at data on direct sales to consumers, especially since they do not even collect such data for the majority of points of sales. On the other hand, the marketing manager revealed that they perform marketing activities because they think these affect consumer sales, but the participant did not know how these activities affect consumers. Due to this truncated view of the problem situation, participants were looking for a familiar explanation for stagnating sales, such as occasional product quality deficiency or the lack of points of sales to enter in the market. However, simulation of these aspects failed to explain sales behaviour of their product. Introduction of the model in Figure 5.6 drew the discussion away from production and client sales aspects towards consumer orientation. This aspect, which was initially hidden from their truncated view of the problem, allowed simulation of their sales problem. In a series of GMB meetings, the participants managed to shift their worldview from thinking about strategy levers aimed at production and client sales improvement, towards strategies aimed directly at consumers. The shift from production-driven to consumer-driven product management has been recognized as one of the factors in assuring product success in food systems (Meulenberg and Viaene, 2005). Consumer orientation of a company implies that the company's activities need to be focused on satisfying consumers' needs (Davčik and Rundquist, 2012). GMB sessions increased participants' understanding of the mechanisms by which they can influence consumer sales, which provides an opportunity to improve future strategies by using that newly acquired knowledge.

4.2. The likely causes of stagnating sales of a food product in the PLC

Model simulations indicated that to prevent stagnation of sales, the company needs to continue to continuously incentivise existing consumers and attract new consumers by offering product discount. This behaviour is in line with PLC literature explaining that non-durable products, such as food products, often have a cycle-recycle PLC sales curve (Kotler, 2003; Midgley, 1981). The cycle-recycle curve has multiple consecutive cycles of growth and decline in sales (Kotler, 2003). In the first cycle, strong product promotion leads to the consumers' initial buying decision and to the first peak in sales. However, only part of the initial buyers continue buying the product regularly, which is a possible reason for the decrease in sales until the next cycle of strong promotion and (re-)initial buying decisions of consumers who stopped buying the product in the previous cycle (Midgley, 1981). This explanation corresponds to the SFD in Figure 5.6, where potential consumers buy a product after some promotional activities, and become non-loyal consumers. However, only a small number finally becomes loyal consumers, while others go back to the stock of potential consumers until they are triggered again into buying the product because of the company's promotional activities. This also corresponds to the GMB participants' statements. For example, their consumers want to try new products, instead of being loyal to only one. Moreover, they stated that promotional activities, such as product discounts, have a high impact only on short-term sales increase.

Another possible cause of problems with the sales of the healthy snack product comes from the literature on product cannibalization. Cannibalization represents "the extent to which one product's consumers are gained at the expense of consumers of other products of the same company" (Guide and Li, 2010, pg. 551). Launching new products is an important strategy to sustain company growth (Barczak and Kahn, 2012), and some of the GMB participants stated that more new products need to be launched to improve the overall sales of the company. However, the model simulations in Figure 5.8 suggest that launching new products might not always be the best strategy, as it might affect the sales of existing products. This is particularly relevant when it causes consumers to switch from buying an older product to buying a new product. Any new product will take away part of the sales of existing products on the market (Srinivasa et al., 2005). The model behaviour indicates that even small market share loss (e.g., 2.5%) resulting from product cannibalization causes a substantial decrease in sales in the long-term. Consumers who are not loyal are particularly susceptible to switching between similar products (Meredith and Maki, 2001). According to the scenario in Figure 5.7, a bigger portion of consumers of the product in this study apparently belongs to non-loyal consumers. Moreover, cannibalization is especially likely to occur when a newer product is a line extension, i.e., when the two products fulfil the same consumer need and attract the same consumer segments (Guide and Li, 2010; Meredith and Maki, 2001). This is particularly relevant here, since product line extensions have been the main type of company's new product introductions (Horvat et al., 2019).

4.3. Usefulness of the GMB approach in supporting team collaboration in this study

The GMB approach in this study was useful in increasing participants understanding of the potential causes of stagnating sales of their product, and in supporting team collaboration. Before the GMB started, participants indicated a low frequency and quality of communication between the team members. GMB sessions in this study were particularly successful in improving team communication, and in generating insight and shared vision. Participants stated that the best features of the meetings were group interaction and discussing the problems. The first positive impact of the GMB on cross-functional team collaboration was accomplished already early in the process. After the second GMB session, the company increased communication frequency by scheduling weekly meetings between technical and marketing personnel. Communication between technical and marketing personnel is an important element of cross-functional team collaboration (Stewart-Knox and Mitchell, 2003). High level of communication among team members allows knowledge and experience sharing, which leads to shared vision and understanding of the problem and contributes to equal commitment in decision-making processes (Açikgöz, 2017).

On the other hand, GMB's usefulness in increasing commitment to the solutions was somewhat lower. The commitment of the participants in facilitated modelling sessions can be enhanced by allowing participants to co-construct an SD model, which contributes to achieving ownership over results (Rouwette, 2011). In this GMB process, the perceived ownership could have been lower for two main reasons. Firstly, the authors suggested the consumer structure in Figure 5.6 due to the lack of participants' understanding of their consumers. Secondly, there was an unequal participation throughout the GMB process, as two participants only joined the first two GMB sessions. They did not provide data necessary to formalize the production planning and quality sectors of the model. The fact that not all participants joined all the sessions was also stated by participants as one of the disappointing features of the sessions. Potential reasons for the lack of contribution by some participants could be a lack of interest combined with more pressing work issues and a geographical distance (the factory and the headquarters of the company where the sessions were held are 100 km apart).

4.4. Reflection on the ability of the model to represent reality

The participants stated that the model structure appropriately represented their consumers' buying behaviour. To produce the reference mode behaviour in figure 5.2, based on the model structure in figure 5.6, DELAY1 function of Vensim software was used to formulate some variables (i.e., losing loyal consumers, non-loyal consumers forgetting rate, and competition consumers forgetting rate). The use of this function has a hidden impact, which affects the ability of the model to accurately represent reality (see an explanation in Supplementary material 4). To avoid this, the delay function could be removed. However, without it the model ceases having the ability to produce reference mode behaviour. Without the DELAY1 function, simulations of previously reported scenarios lead to similar conclusions regarding the sales rate:

1) A 20% product discount for 3 months leads to a short peak in sales rate, after which the sales rate slightly decreases compared to a simulation without a discount. This temporary increase in the sales rate occurs mainly due to the existing non-loyal and loyal consumers' increased purchase of products. A permanent product discount leads to a permanent increase of sales due to a continuous increase in numbers of non-loyal and loyal consumers.
2) Cannibalization of 0.4 and 2.5% reduces the sales rate throughout the whole run due to reduced winning of non-loyal consumers, which also leads to less loyal consumers over time.
3) Quality issues that affect a low percentage of consumers (i.e., 1%) do not lead to a substantial decrease in sales over time since this does not affect a high percentage of loyal consumers. However, higher percentages of affected consumers (i.e., 10%) over two months will negatively affect sales over a long time due to high numbers of consumers who stop being loyal.

The model building process was useful for participants to improve their communication, insight and shared vision of the problem during GMB sessions, compared to their regular meetings.

However, the structure of the model needs to be further refined to represent behaviour of the healthy snack product sales to improve understanding of the impact of proposed scenarios on the sales rate. This should be done, firstly, by reviewing existing literature on the dynamics of consumer behaviour, followed by repeated GMB sessions with the problem owners to not compromise participants' model ownership. Behaviour in figure 5.2 could potentially be explained by the Rogers' (2003) diffusion of innovations theory and five groups of product adopters (i.e., innovators, early adopters, early majority, late majority, and laggards). However, diffusion of innovations theory was not originally based on sales of consumer non-durables and there is a need to empirically confirm under what conditions it can realistically explain a potential cycle-recycle sales behaviour of a food product. Moreover, Grunert (2005) emphasizes the importance of differentiating between experiences preceding the first and future purchases of individuals, while factors such as rejection upon first trial and boredom after longer could also have an impact on how long people remain consumers of certain products (Rogers, 2003; Zandstra et al., 2000).

5. Conclusions and future work

The group model building approach presented in this study was successful in improving team-collaboration. The model simulations indicated that to prevent the stagnation of sales the company needs to continue offering product discounts to incentivise new and existing consumers into buying their product. Moreover, cannibalisation of the healthy food product by launching similar new products could be another threat to the growth of product sales. Finally, the GMB approach in this study was assessed as more successful in increasing the understanding of the problem of stagnating product sales, compared to the similar meetings where this problem was discussed. GMB supported team collaboration by increasing participants' insight into the causes of the problem, by improving communication among them, and by creating a shared vision about the problem.

The sales problem was conceptualized from multiple perspectives (i.e., marketing, sales, production, and quality). Future model improvements could involve conceptualizing the effect of social media promotion and of specific consumer attitudes on winning consumers, elaborating product quality to involve various product attributes (e.g., texture, packaging), and further expanding the competition sector. Improvement could be made by collecting more accurate consumer data, by performing an extensive consumer research, which could support an in-depth understanding of different consumer categories. Furthermore, similar models of other company's products could be built to study the effect of product interactions on sales.

Lastly, the usefulness of GMB approach in supporting team collaboration to understand the problem of stagnating sales of a food product was appraised based on four factors (insight, communication, shared vision, and commitment). Future research could move towards uncovering if any other factors are important in supporting team collaboration, and investigate the mechanisms through which these factors lead to positive outcomes after GMB. Moreover, different study designs (e.g., pre- and post-test survey, and a follow-up survey after some time has passed from the last GMB session) could show the extent of cross-functional team collaboration improvement from the beginning to the end of the GMB process and the extent of resilience of improvement in team collaboration due to the GMB process.

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Chapter 6

General discussion

6.1. Background

Food companies have been facing a challenge in developing new food products and in making them successful, due to the complex nature of the new food product development process (NPD) and the product life cycle (PLC) (McCarthy et al., 2006). The complexity of NPD and PLC is a result of the involvement of multitude of actors in and outside the food company (van Trijp and Steenkamp, 2005; Earle et al., 2001). Moreover, the interconnectedness of factors that affect product success complicates understanding of their impact on product success over time. Past research gave suggestions for improvement by identifying the most relevant success factors, by proposing a structured stage-gate approach to managing NPD, or by recommending an integrated approach to product development (e.g., Straus, 2009; Moskowitz et al., 2009; Evanschitzky et al., 2012). However, none of those approaches aimed at explicitly representing the complex and dynamic nature of food product performance evolving over time. This thesis employed systems thinking and system dynamics approaches to identify feedback processes relevant to understand the dynamic aspects of food product success. The methodology also aimed at understanding the problems and finding solutions in an integrated way (i.e., by combining the perspectives of the three main actors in developing new food products: technology, marketing, and consumer research).

The discussion starts with a description of the main findings, followed by theoretical contributions of the PhD project, methodological considerations, and implications for future research. Finally, recommendations for practitioners and main conclusions are described.

6.2. Main findings

To understand to what extent companies make informed decisions that affect product success and if they use methods appropriate for complex dynamic problems, we performed a survey among European food companies, described in Chapter 2. We examined to what extent marketing, R&D, and consumer research professionals use three different types of consumer data (i.e., consumer involvement, food trend, and environmental factors data) in different phases of product's life (NPD and PLC), and what data collection methods they use. We categorized consumer data into three types based on time frame, which represents the relative length of the period in which consumer data are obtained. Consumer involvement data represent the shortest time frame, as they usually require data collection at one point in time, while data on environmental factors cover the longest time frame, sometimes even decades. The empirical study described in Chapter 2 showed that the professionals in our study extensively use all three data types in NPD, while their use is significantly lower in the PLC. This could indicate that the respondents assess the degree of fit between a product and consumers' needs to a lesser extent once products are on the market. Moreover, while respondents use formal methods to collect consumer involvement data (e.g., focus group, consumer surveys, sensory tests), this is not the case for data on food trends and environmental factors. Currently, these types of data are the most frequently collected through secondary sources (e.g., newsletters, reports, food fairs, and the internet). Lastly, respondents rarely employ simulation-modeling methods, such as system dynamics, which could indicate a lower consideration of dynamic feedback mechanisms influencing product success.

To increase the understanding of food product performance from a dynamic perspective, a systematic literature review was performed, which is described in Chapter 3. The review revealed variables relevant for dynamic assessment of food product performance during its product development and life cycle. The variables were the basis for designing three means-criteria diagrams from the perspectives of technology, marketing, and consumer research. The means-criteria diagrams helped in identifying the feedback loops, which represent the sources of change in product performance. A feedback loop is a cyclical path where an output of a variable triggers changes in other variables in a cause-effect chain, which in turn becomes an input to the initial output variable. A reinforcing feedback loop increases the initial change, while a balancing feedback loop counters the initial change. We identified four balancing feedback loops related to: 1) product quality variation, 2) capability of the technology function, 3) intensity of the competitive response, and 4) effect of distribution and sales functions on competitive response. Moreover, we identified seven reinforcing feedback loops related to: 1) newness of product characteristics, 2) marketing mix suitability, 3) capability of the marketing function, 4) influence of distribution and sales departments on market share, 5) consumer product familiarity, 6) effect of quality expectations on consumer satisfaction, and 7) effect of experienced quality on consumer satisfaction. Since the marketing, technology, and consumer research functions do not work in isolation, the three means-criteria diagrams were used to develop an integrated framework for dynamic assessment of performance of a new food product. The integrated framework captures the dynamic nature of the new food product performance in a single image (see Figure 3.5 in Chapter 3). It shows the cause-effect relationships between the actions of one function in a firm and the consequences of these actions for performance, as well as the consequences for other functions. Although uncovered feedback loops give an indication of possible changes in product performance, the extent of the effect of feedback loops on the change in performance and the period in which the change occurs should be estimated by developing a simulation model, which was further explored in the next chapters. Thus, Chapter 3 served a purpose of providing knowledge about potential feedback loops related to food product performance that could be represented in system dynamics (SD) simulation models.

The following two chapters (Chapter 4 and 5) present two different ways to build and use SD models to understand the dynamics of food product performance and the complexity of NPD and PLC in two different cases. The study in Chapter 4 aimed at investigating the dynamic adoption process of insect-based food in the Netherlands to demonstrate how to develop a system dynamics model based on a structured literature review and existing theories. We performed a structured review of the literature on edible insects and applied the innovation of diffusion paradigm and the Bass diffusion model (Rogers, 2003; Sterman, 2004) to develop an adoption model for insect-based food. The internal model structure, represented as a stock and flow diagram, was able to explain the adoption process of insect-based food from a narrow perspective, since past studies on insect-based food mainly explored factors related to consumer psychology of choosing insect-based food. Multiple other stakeholders could also influence the process of food adoption, such as food companies competing on the market and governments setting regulations. Simulations revealed that the diffusion of insect-based food, such as an insect-based burger, would be a long process under the currently reported practices in the Netherlands. In scenario 1, we analysed the effect of increase of word-of-mouth and promotion on the adoption rate. While promotion is important to increase the initial familiarity of the population with such products, the main mechanism that can strongly affect diffusion of such food is word-of-mouth, occurring after a positive tasting experience. In scenario 2, we studied the effect of increased sensory quality on the adoption rate, and in scenario 3, we studied the effect of increased likelihood to adopt. The simulations revealed that to observe a substantial change in adoption under increased adoption likelihood, there is a need of combining it with an increase in sensory quality of the product. The SD approach was beneficial in uncovering knowledge gaps that can guide future research, such as the need to understand the mechanisms of negative word-of-mouth, the factors influencing adoption of insect-based burgers by people who initially reject it, and to understand the influence of factors such as availability and promotional activities.

The study in Chapter 5 investigated a participatory approach to build an SD model, called group model building (GMB). A system dynamics model was built together with people from different functions (marketing, sales, production, and quality) in a case company to understand the causes of stagnating sales of their healthy fruit snack. The study explored the usefulness of the GMB approach in supporting cross-functional teams in making PLC decisions in the food industry. In the beginning of the GMB process, the participants had a truncated view of their problem, and they were looking for possible causes of stagnating sales in the aspects that were familiar to them (e.g., product quality, entrance in points of sales). In a few series of GMB meetings, the participants managed to shift their worldview from strategies aimed at production and supply towards strategies aimed directly at consumers; an aspect that they did not understand well before the GMB sessions. The developed model revealed that their product sales are oscillating, with multiple consecutive cycles of increasing and decreasing sales. This behaviour could not be explained without understanding their consumers. At one point in time, the company attracts many non-loyal and loyal consumers through marketing campaigns, which causes an increase in product sales. However, there are feedback loops that lead to the loss of one part of those loyal and non-loyal consumers (e.g., because of a negative experience with the product or because consumers switched to some other product), which leads to a delayed effect of sales decrease. This resulted in the observed oscillating pattern. Some of the GMB participants stated that new products should be launched to attract more consumers and improve overall sales of the company. However, the model simulations suggested that launching new products might not always be the best strategy, as it might influence sales of existing products. This is particularly relevant when it causes consumers to switch from buying an older product to buying a new product. Lastly, according to a post-test survey, the GMB approach was successful in increasing participants' insight into the causes of the sales problem, in improving communication, and in creating shared vision about the problem. GMB sessions allowed participants to discuss their sales problem as a team of people with different functions.

6.3. Theoretical contributions

6.3.1. Empirical evidence on the use of consumer data in food companies

There are many studies on NPD, but they rarely focus on food products and food industry. Some textbooks focus specifically on food (e.g., Earle et al., 2001; Jongen and Meulenberg, 2005; Moskowitz et al., 2009), but there has been a lack of empirical data related to NPD and PLC in the food industry. Consumer research has a particularly important role in food product development. It uses a variety of metrics and analyses in order to measure consumers' reactions to products and concepts (e.g., Moskowitz and Saguy, 2013). To perform such measures, consumers need to be involved to some extent in the measurement process. The data obtained by such measures is the so-called consumer involvement data. In Chapter 2, we recognized two more categories of consumer data that companies could use in product development, i.e., food trends and data on environmental factors which relate to socio-cultural, demographic, economic, and technological aspects of food choice (van Trijp and Steenkamp, 2005; Meulenberg and Viaene, 2001). The study in Chapter 2 provided empirical evidence on the use of those three types of consumer data in different phases of the product's life (i.e., NPD and PLC) by food companies. Moreover, results provided insight in the most frequently used tools and methods to collect data used by the participating European food companies. The companies indicated a limited use of tools and methods to collect consumer data. Moreover, the data were collected mainly in the NPD phases and scarcely in the PLC phases. In some cases, the used methods and tools were not the most appropriate ones to enhance food product success. For example, the most frequently used methods to obtain consumer involvement data are focus groups, consumer surveys, and the use of the internet, and magazines (Figure 6.1). These methods provide a limited guarantee of product success. Firms may have less control over their product's success when employing only these methods (Geyer et al., 2018; Janssen & Dankbaar, 2008; Wind & Mahajan, 1997).

Furthermore, food product management in NPD and PLC is complex due to the collaboration of multiple functions in multiple phases of product's life (McCarthy et al., 2006; van Trijp and Steenkamp, 2005). The frequently used tools and methods in practice are not specifically suitable for complex processes, as they do not capture those interdependencies and their impact on product success (Horvat et al., 2019; Sterman, 2004). Moreover, such methods are not capable to tackle the complex problem of food success from a dynamic perspective (e.g., Schmidt and Gary, 2002; Chapter 3 of this thesis). There is a need for a different approach in food product management in European food companies, which would allow a better understanding of the complexity of this system and its impact on food product performance over time.

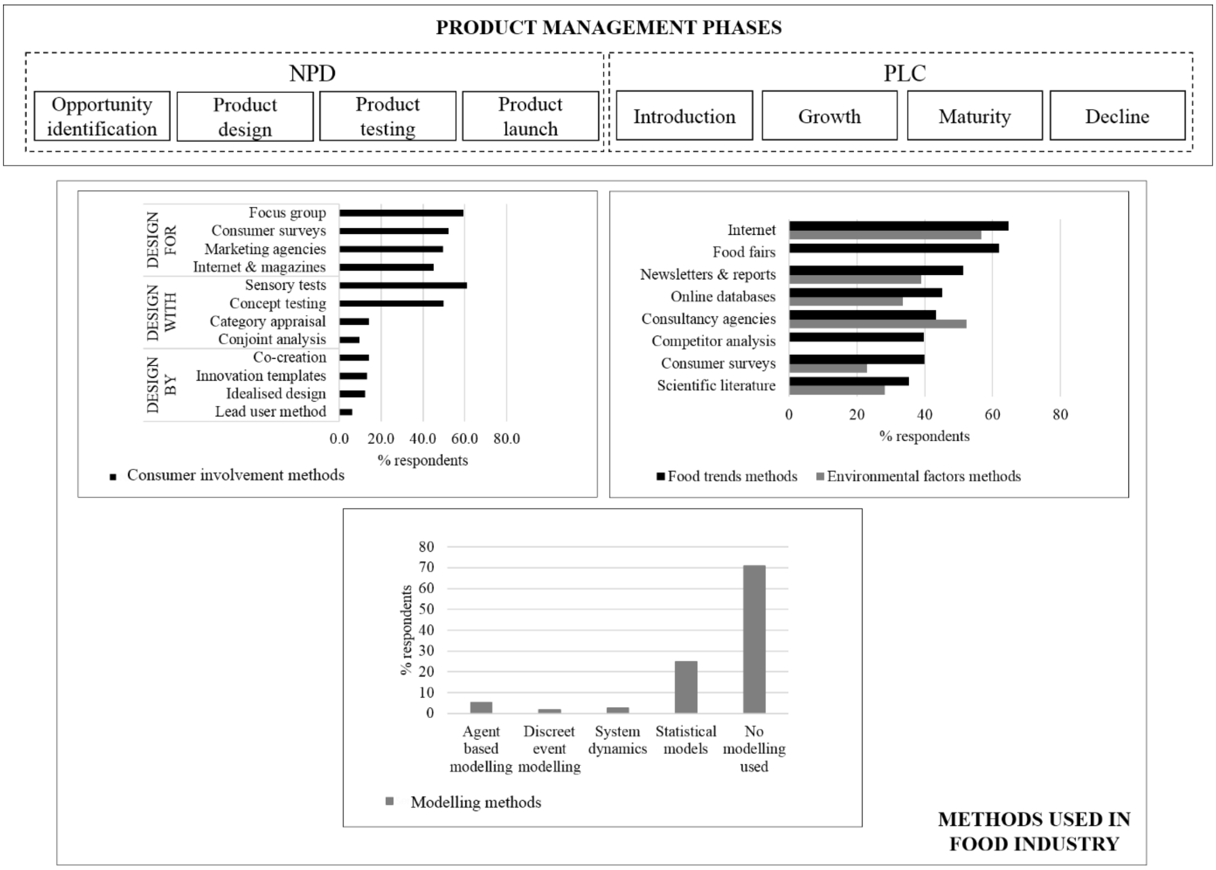

Figure 6.1. *Methods used in food product management in European food companies.*

6.3.2. Towards an integrated approach to food product performance by employing systems thinking

To assure product success, multiple authors stated the need to establish a holistic and integrated approach to product development in general, as well as specific for food (e.g., Sommer et al., 2014; Moskowitz and Saguy, 2013; Straus, 2009; Moskowitz et al., 2006; Khurana and Rosenthal, 1998; Earle, 1997; Brown and Eisenhardt, 1995). Yet, the literature on presenting such integrated approaches is very limited. As one effort, Moskowitz et al. (2009), proposed an integrated approach to food product development. However, they did not explicitly outline the interconnectedness of different functions and their impact on the product success over time. An alternative method for developing such an integrated approach is system thinking. Systems thinking is an approach that enables mapping causal connections in a complex system, and increases understanding of how those causal connections affect system's behaviour over time (Arnold and Wade, 2015; Meadows, 2009). To fill the literature gap, in Chapter 3 we developed three means-criteria diagrams combined into an integrated framework for dynamic assessment of performance of a new food product (Figure 6.2B). The means-criteria diagrams incorporate major performance variables of the three main functions (i.e., marketing, technology, and consumer research, see Figure 6.2A) that play a role in the overall food product performance on the market. They explicitly show interactions between the three functions and the feedback processes that cause changes in food product performance. For example, loops contributing to product quality variation and technology synergy affect meeting quality specifications, loops related to product familiarity, experienced product quality and positive beliefs from past tasting impact consumer satisfaction, and market share is influenced by feedback loops describing the changes in market synergy and market potential. By using the integrated framework and means-criteria diagrams, it is possible to track the impact of one function on another one, and on the overall product performance, which can facilitate tracing the problems and also long-term thinking and reflection on one's actions prior to performing actions in the real world (Enserink et al., 2010; Montibeller and Belton, 2006).

Moreover, understanding the underlying causes of the new food product performance can help in anticipating changes in the external food business environment and adapting to them, which can lead to better decision making and higher chances of product success (van Trijp and Steenkamp, 2005; Sterman, 2004). Organisations such as food firms often tackle problems as they appear, without taking the time to understand the broader context of the organisation and the environment (Schaveling and Bryan, 2018). However, this short-term and narrow view of problems can lead to unintended consequences, which often have a negative impact on performance (Schaveling and Bryan, 2018; Sterman, 2004). For example, if a company develops a new food product, competitors with similar products might soon appear, and the company might need to adapt their products to remain competitive on the market. This forms a feedback process where a company, by making certain decisions, causes the environment to change, and those changes in the environment eventually might affect the three company functions, which was also show in the study in Chapter 5. The integrated framework gives an explicit graphical representation of a multitude of aspects that need to be taken into account when making decisions about food products. Moreover, it shows feedback loops that facilitate understanding of various dynamic aspects of changes in product performance (Kunc, 2012; Barlas, 2009; Sterman, 2004). Although qualitative models increase understanding of the system, they do not give an information about the specific patterns of food product performance over time, which is why simulation models, such as system dynamics (SD) need to be developed (Barlas, 2009).

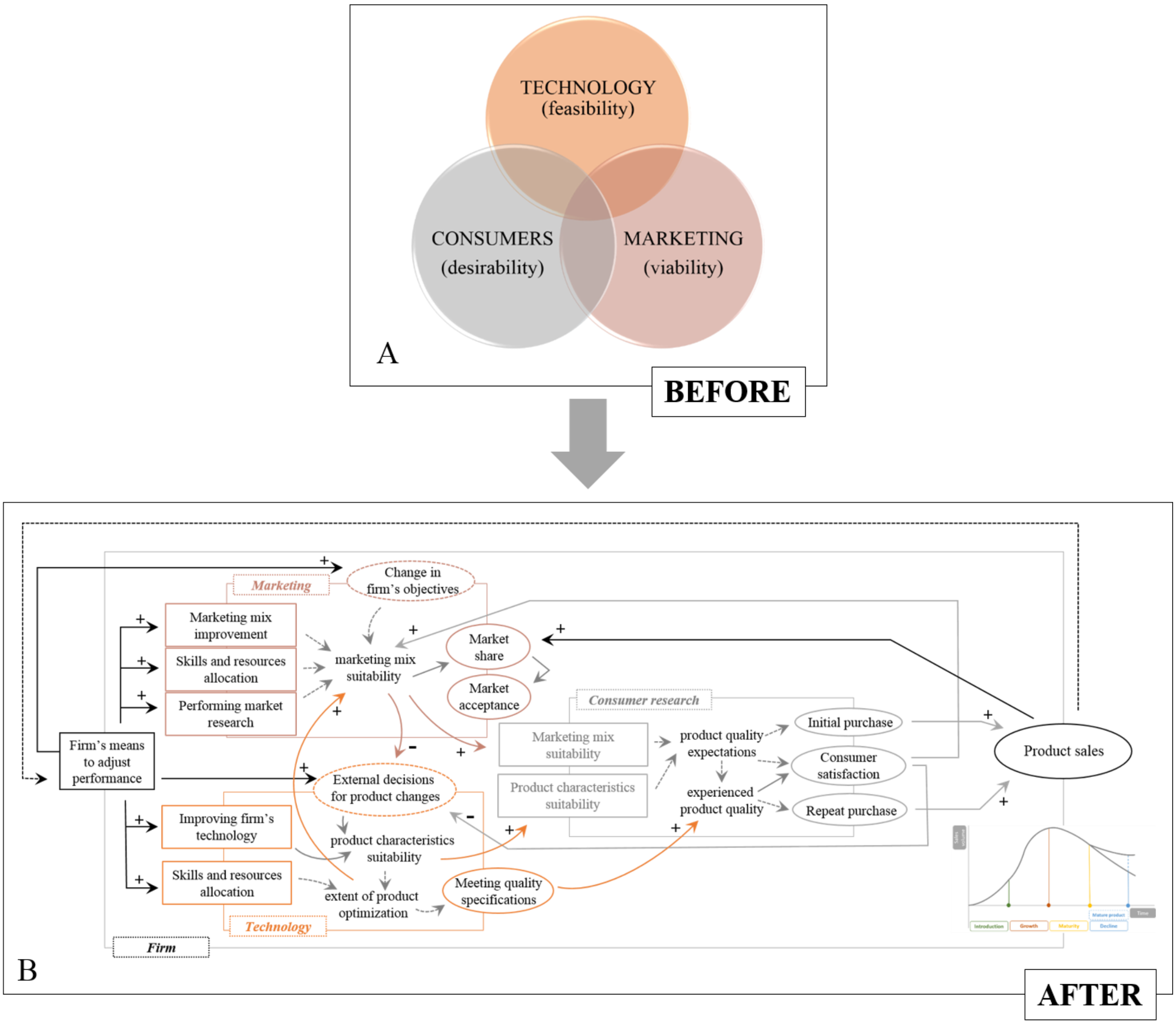

Figure 6.2. *Schematic presentation of the development of an integrated approach to new food product development from the three main functions, i.e., technology, consumer research, and marketing [6.2A], to an integrated framework [6.2B] as developed in Chapter 3, explicitly showing the interconnections between the three functions and their impact on food product performance.*

6.3.3. The need for modeling and simulation to increase understanding of the impact of feedback loops on food product performance

SD modelling and simulation have been rarely applied in the food industry, and to the best of our knowledge, there have been no reported scientific studies on SD modelling and simulation of food product performance. However, such models are crucial in understanding the impact of dynamic mechanisms, i.e., feedback loops, on food product performance over time (Kunc, 2012; Barlas, 2009; Sterman, 2004). People can find it difficult to understand and analyse complex systems, which is why they tend to ignore the complexity or they try to make sense of it in ways that do not fully reflect complexity of the system (Teale et al., 2003). Therefore, complex problems are commonly simplified, which enables a straightforward choice of solutions (Luning and Marcelis, 2006). Qualitative models in Chapter 3 (i.e., means-criteria diagrams) are useful in visualising and increasing the understanding of the dynamic mechanisms in a complex dynamic system (Enserink et al., 2010; Sterman, 2004). However, the actual impact of feedback loops on performance over time can only be estimated by developing computer-simulated models (Sterman, 2004). According to Sweeney and Sterman (2000), decision-makers struggle with simple models even without feedback loops. To illustrate, in Chapter 3, we uncovered eleven feedback loops, which show that the use of computer simulation is crucial in understanding the impact of managers' decisions in food product management. Moreover, the development of quantitative SD models is useful because they allow simulation of different decision scenarios, which can uncover scenarios that will lead to the accomplishment of future goals (Wang and Chuang, 2015). Chapters 4 and 5 of this thesis contributed to the body of literature on quantitative SD modelling and simulation of food product performance.

6.3.4. Employing system dynamics to study adoption of food products

In the past, SD simulation modelling has been used to study various complex dynamic problems. Such SD models are usually based on the SD Bass diffusion model, which has its roots in the diffusion of innovations paradigm and the analytical Bass diffusion model (Sterman, 2004; Rogers, 2003; Bass, 1969). A wide range of adoption studies, based on the Bass diffusion system dynamics model, exist, e.g., adoption of improved maize seed (Derwisch et al., 2016), alternative fuel vehicles (Benvenutti et al, 2017), cell phones (Dutta et al., 2017), renewable energy (Jimenez et al., 2016), golf clubs (Kreng and Wang, 2013), etc. However, the specific topic of food product adoption has not been investigated, and this thesis represents the first example of application of SD Bass diffusion to food products. The Bass diffusion SD model as

Sterman (2004) presented it (Figure 6.3A) was, however, not suitable to represent the process of food product adoption. Sterman's model (2004) has two stocks (potential adopters and adopters) and assumes that potential adopters become adopters of the product if they are triggered by the word-of-mouth of other adopters or by advertising. However, tasting is an important element of food choice (Ruby et al., 2015). If a person tastes a product and does not like it, then that individual will not adopt such a product (Tan et al., 2016). Therefore, in the case of adoption of insect-based products, potential adopters, if they are influenced by advertising or word-of-mouth, will first become potential tasters (see Figure 6.3B). Moreover, potential tasters will only become adopters of a product if they exhibit a certain level of likelihood to adopt, which is based on past tasting experiences of similar products, and if they like the sensory quality of the specific product (Tan et al., 2016; Tan et al., 2015). Furthermore, the SD model in Chapter 4 assumes there is one other category of people, i.e., rejecters, who will not adopt the product if they did not like it after tasting it (Rogers, 2003). The original Bass diffusion SD model was therefore extended to capture these specific elements inherent for consumption of new food (Figure 6.3B).

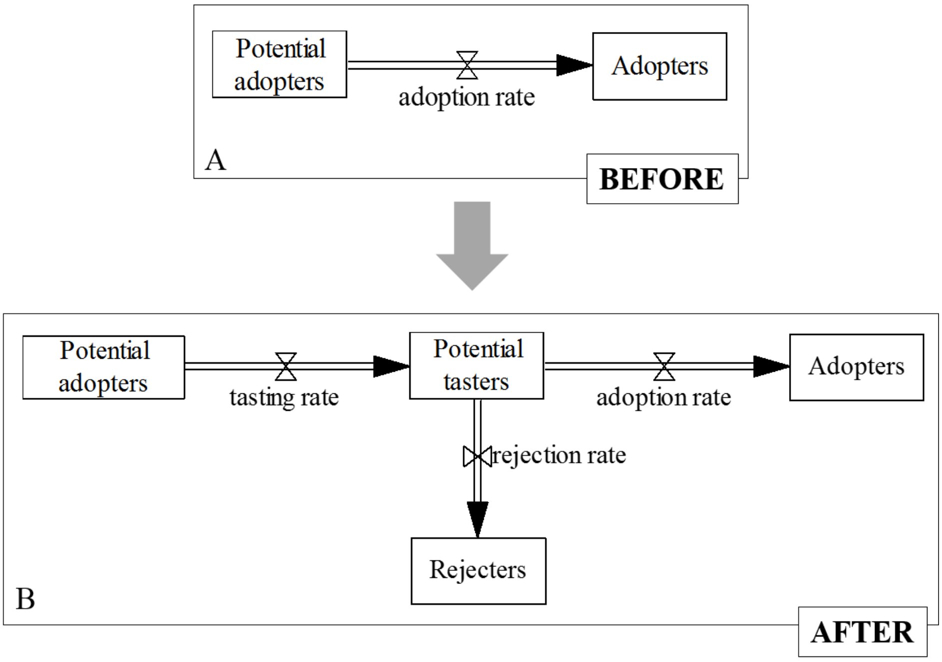

Figure 6.3. *Original SD Bass diffusion model (6.3A) and an extended SD Bass diffusion model (6.3B) to study adoption of food products in Chapter 4.*

The model developed in Chapter 4 is a theoretical model of adoption of a food product, which was based on the review of edible insects literature, the diffusion of innovations paradigm, and the Bass diffusion model. However, SD modelling is frequently performed by directly involving problem owners in the model building process (Zagonel, 2002), which can also be applied to study food product success.

6.3.5. Group model building (GMB) improves understanding of the problem of stagnating product sales in a cross-functional team in food industry

Involvement of clients in the process of building a system dynamics model has been important from the early days of the system dynamics field (Zagonel, 2002). The clients' contribution lies in conceptualizing the model, but also in establishing the model validity to gain confidence in the model's effectiveness in representing the client's system (Forrester, 1961). Chapter 5 described a GMB project in a food processing company, which aimed at developing an SD model to increase participant's understanding of the causes of stagnating sales of a healthy fruit snack. The developed model represented a "micro-world" of consumers who buy the company's healthy fruit snacks in a specific market. SD models represent "micro-worlds" when a problem is clear from the start and the aim of GMB is to capture important elements of the problem in the model to solve it, which was the case in this project (Rouwette and Vennix, 2006; Zagonel, 2002). To build system dynamics models as "micro-worlds", information about decision rules is required, and that information is usually not available in written form, but inside of people's minds in the form of mental models (Sterman, 2004; Forrester, 1992). The GMB process described in Chapter 5 allowed participants from different functional departments of one company to share pieces of information through a series of open discussion, which facilitated mapping underlying causes of stagnating product sales and uncovering potential solutions.

The GMB process described in Chapter 5 was particularly successful in generating more insight and more quickly, and more structured communication. Consequently, it generated better-shared vision or consensus of the problem, compared to the normal meetings where the same problem was discussed among company staff participating in GMB. People's cognitive limitations make them focus on parts of the problem, instead of the whole system, which ends up with piecemeal solutions to complex problems (Vennix, 1996). Throughout the process of GMB, the participants contributed with their partial view of the problem to build a system dynamics model of the problem as a whole (Zagonel, 2002). The structured GMB approach and the presence of a facilitator supported sharing participants' mental models. Moreover, the participants needed to justify their opinions, and to ground their view in data, which could have had a positive impact on the outcome of the GMB project (Zagonel, 2002; Sterman, 2004).

Multiple studies in the past reported mainly positive outcomes of GMB in understanding and solving complex dynamic problems (see extensive reviews by Scott et al. (2016), and Rouwette et al. (2002) for an overview of past studies). For example, Rouwette (2011) performed three GMB case studies in a government setting and reported GMB's positive impact on communication and commitment of the clients. Scott et al. (2015) performed a GMB study with a governmental agency. They showed that, compared to normal meetings, GMB sessions generated more insight, resulted with better communication, and more consensus. However, none of the past studies reported GMB in a food company, or more specifically, related to an issue of food product performance. In this thesis, GMB was performed in one food company, which was the first example of applying GMB to a complex problem of unsatisfactory food product performance. Our research demonstrated that this approach could be helpful in solving complex dynamic problems related to understanding product performance in the food industry. Future research could move towards employing the GMB approach to other complex dynamic issues in food industry.

6.4. Methodological discussion

6.4.1. The use of systematic literature reviewing principles to build complex dynamic models

A systematic literature review was performed to develop means-criteria diagrams and an integrated framework for dynamic performance of food products in Chapter 3. More specifically, we performed a configurative literature review by following the guideline set out by Gough et al. (2012a). Configurative literature reviews aim at organising findings of studies, and require an iterative process of collecting and synthesising qualitative data to gain new conceptual or theoretical understanding (Gough et al., 2012a). By applying the principles of systematic literature reviewing, we were successful in finding relevant variables, their causal connections, and feedback loops as sources of dynamic behaviour to develop means-criteria diagrams. We considered all the sections of the reviewed papers in our analysis, instead of looking only at the results section (which is often the situation in aggregative literature reviews, since they aim at collecting empirical data to test if a theory or a concept works) (Gough et al, 2012b). In configurative reviews, the priority is on collecting qualitative data to generate a theory (Harden and Gough, 2012). Moreover, qualitative data, such as the data we collected in Chapter 3, is considered as a rich source of knowledge for conceptualizing system dynamics models (Forrester, 1992). Unfortunately, SD studies often do not follow rigorous methods of collecting qualitative data for model conceptualization. The study in Chapter 3 is a rare example of employing systematic literature review principles to conceptualize a model. Applying the principles of systematic literature reviewing, which were used to conceptualize means-criteria diagrams in Chapter 3, could become a constituent part of data collection when developing theoretical qualitative and quantitative SD models.

6.4.2. The choice of system dynamics simulation modelling to study dynamic food product performance

System dynamics modelling starts by identifying and defining a problem, which becomes the basis for the development of a conceptual model of the system and the problem situation (Sterman, 2004). Due to the complexity of the problem, models represent simplifications of the real world situation, and they contain various assumptions (Sterman, 2004; Behdani, 2012). Some of the assumptions and simplifications are imposed due to the choice of system dynamics as a modelling method (Behdani, 2012). System dynamics models belong to the group of aggregate models (Sterman, 2004). In the models in Chapters 4 and 5, this implies that consumers are studied as a perfectly mixed collection of individuals with an aggregated behaviour. Therefore, their individual behavioural characteristics are not presented and numerical values of variables correspond to average values of the complete social system that was studied. Studying consumers from an aggregate perspective is not necessarily in line with the contemporary consumer-oriented product development where understanding food choice of individual consumers is a major concern (Varela and Ares, 2018). Nowadays, companies put a lot of effort into understanding different types of consumers and use various segmentation methods to develop and launch products for specific consumer segments, e.g., conjoint analysis, hierarchical cluster analysis (Varela and Ares, 2018). Köster (2003) claimed that the average consumer does not exist, stressing the need to consider individual differences in consumer behaviours and the variables that underlie them (Varela and Ares, 2018). Therefore, in the case where a more detailed understanding of consumers is required and data that are more specific exist, other modelling methods can also be useful. For example, agent-based modelling is individual-oriented and it allows a more detailed representation of interaction between consumers, who can also make autonomous decisions (Behdani, 2012). However, in some situations, such as in the studies in Chapters 4 and 5, there can be a lack of data and theoretical underpinnings to represent individual consumers. For example, according to Chapter 2, specifically small companies use less consumer data. In such situations, system dynamics could be a useful methodology, since it can overcome the lack of data related to individual consumers or consumer segments.

7. Implications for future research

7.1. Future role of consumer research in understanding food product performance over time

Moskowitz and Saguy (2013) called for redefining the role of consumer research in food companies. They suggested that consumer researchers should become more involved in business issues in food companies. Understanding mechanisms that affect product performance over time is one such business issues. There is a need to develop understanding of how consumer research can better support the improvement of product performance over time. For example, in Chapter 4, we showed that there is still no clear understanding of the mechanisms of (negative) word of mouth, adoption of products by people who initially reject it, and the effect of product availability on adoption. Moreover, Chapter 5 explored concepts of repeated purchase by separating consumers into non-loyal and loyal. However, more theoretical and empirical research on food products is needed to characterize these two types of consumers and to better understand aspects of first and repeat purchase, but also of product boredom, which makes loyal consumers to stop buying products. Furthermore, since consumers change over time (van Trijp and Steenkamp, 2005), there is a need to establish longitudinal consumer data collection to observe those changes and to see the impact of changes on consumer food choice and on food product performance.

7.2. Need for interdisciplinary research in studying consumer food choice

Food products are complex systems consisting of a multitude of product attributes, which are dynamic in nature (e.g., safety, sensory quality, properties of raw materials, process parameters) (Luning and Marcelis, 2006, 2009). Once products appear on the market, consumers' individual characteristics come into play, and together with the complexity of products, contribute to the overall complexity of consumer choice and to product performance (Kaul and Rao, 1995). According to Rozin (2006), to better deal with complexity of food choice, individual researchers have compartmentalized various aspects of food choice. Nowadays, different aspects of consumer food choice are studied by various disciplines, such as marketing, consumer, and sensory scientists. Sensory research aims at measuring, analysing, and interpreting responses to products perceived through the senses of sight, smell, touch, taste, and hearing (Moskowitz et al., 2012; Stone and Sidel, 1993). Consumer researchers apply psychological theories to study consumer behaviour and deal with how consumers make choices among various products (Grunert, 2015). Marketing, on the other hand, takes an economic perspective and is concerned with marketing mix (product, price, place, and promotion), which needs to be established to encourage consumers to buy products (Grunert, 2015). This compartmentalized way of performing consumer research does not represent realistically the consumer decision-making process. To tackle the complex challenges of consumer food choice throughout the whole product's life cycle, future research needs to be "more interdisciplinary and realistic" (Varela and Ares, 2018). "Real world problems rarely regard disciplinary boundaries" (Carr et al., 2018, pg. 35). Scientists from the three disciplines should establish ways of working together to solve the complex problem of consumer food choice and its impact on the overall product performance.

7.3. Systems thinking and system dynamics to study complex problems in the food science field

Since real world problems, such as food product performance, are complex, to study them, there is a need to use approaches that allow researchers to cope with and embrace the complexity. Systems thinking and system dynamics are such approaches. This thesis focused on the problem of food product performance from the perspective of three functions (marketing, technology, and consumer research). However, the study of food product performance could be expanded by involving other food company functions, such as sales, logistics, production, finances. etc. Moreover, external actors could be included, such as competition, suppliers of raw materials, food authorities, or retailers. In that way, the influence of the whole food production system on product performance could be studied. Systems approach was previously applied to understand the impact of business environment on food safety performance (e.g., Kirezieva et al., 2013; Luning et al., 2011). Furthermore, systems thinking could be used on other dynamic problems in the food science field. On a smaller scale, system dynamics could be used to map and simulate biochemistry of digestion and absorption in human body after ingestion of specific food components. Researchers could develop dynamic feedback structures of such processes. By comparing the simulated and the empirically measured output of such processes, researchers could test the validity of their assumptions regarding the mechanisms driving the change in the output (e.g., Owen and Griffiths (2013) modelled plant metabolism). Moreover, the impact of diets on the health status (e.g., nutrient deficiency) of individuals and populations could be conceptualized and simulated. Similar research has been performed to study obesity (e.g., Fallah-Fini et al., 2014). On a higher scale, the impact of factors such as climate on the occurrence of safety issues throughout the food supply chain could be studied. Similar studies have been performed in relation to agricultural risks (e.g., Rosenzweig et al., 2014). These are only some examples of complex problems occurring in the food production chain that can be studied by employing systems thinking and system dynamics.

8. Recommendations for practitioners

Scientific literature showed high rates of new product failure in the period from 1965 to 2010, with consumer goods having one of the highest failure rates (Castellion and Markham, 2013). High failures of new products have been occurring due to the high complexity of product development. According to Luning and Marcelis (2006), high levels of ambiguity, resulting from the lack of understanding, and high levels of uncertainty, caused by the lack of information, are sources of complexity. Therefore, to increase their chances of food product success, food companies need to increase their understanding of causes of product failure to reduce ambiguity and use appropriate data to reduce uncertainty in decision-making.

To increase understanding of the causes of product failure, food companies can use the integrated framework for dynamic assessment of performance of a new food product and three means-criteria diagrams in Chapter 3. Most people are not able to deal adequately with dynamic complex issues, such as food product performance, without the help of models (Pruyt, 2013). This is because socio-technical systems contain multiple interconnected feedback loops, which are causing change in product performance over time. Therefore, due to the bounded rationality of decision makers and the complex nature of problems, it can be difficult to understand the problem, to make good estimations of the impacts of certain decisions, and to formulate solutions. The integrated framework facilitates comprehension of the consequences of practitioners' activities on product performance at any phase of NPD or PLC. A well-organized NPD processes (such as stage-gate) is important for developing successful products, but it mainly facilitates single loop learning. Single loop learning focuses on "changing methods and improving efficiency to obtain established objectives (i.e., "doing things right")" (Cartwright, 2002, pg. 68). On the other hand, the integrated framework, and the means-criteria diagrams are a basis for double loop learning. Double loop learning aims at "teaching people to think more deeply about their own assumption and beliefs (i.e., "doing right things")" (Cartwright, 2002, pg. 68). Every manager has their own experience and knowledge based on which they make decisions, i.e., mental models. To be able to improve their strategy, managers need to improve their mental models so that they represent reality as best as possible (Morecroft, 1994). The integrated framework and means-criteria diagrams allow managers to test if their mental models are aligned with scientifically based causes of changes in food product performance over time. It also helps them to include other perspectives and to extend their mental models. Yet, practitioners should not stop at using only the integrated framework and means-criteria diagrams from Chapter 3. The actual impact of feedback loops presented in the diagrams on food product performance can only be shown if a simulation model is developed (Wolstenholme, 1999). Using only qualitative models can lead to inappropriate insights and wrong inferences about product performance (Wolstenholme, 1999).

According to results in Chapter 2, SD has rarely been used in European food companies, while statistical models have been used more frequently in European food companies. For example, regression models can be used to test the impact of decisions on complex dynamic problems to some extent (Barlas, 1996). However, it is difficult to use such models to generate insight about the mechanisms that cause a certain behaviour over time, since they do not show the intricacy of causal relations between variables (Wang and Chuang, 2015; Barlas, 1996). This type of models is called black-box models. They are often correlational and purely data driven and their purpose is to match their output to the historical performance, and to forecast the future performance of the system (Barlas, 1996). On the other hand, white box-models, such as system dynamics, represent a "theory" about the real system and they show how the system actually operates (Barlas, 1996). However, black-box and white-box models can be used together to support each other and to provide further insights. Therefore, next to their usual forecasting methods, companies could invest in developing SD simulation models of persisting complex dynamic problems to uncover their underlying causes. Existing data and knowledge from mental models of managers can be exploited to develop system dynamics models, which would have a purpose of “virtual laboratories”. Such “virtual laboratories” would facilitate learning about complex mechanisms underlying product performance (Pruyt, 2013). Additionally, they would be a useful tool to test the impact of managers’ decisions before undertaking activities in the real world. Moreover, of great value would be that SD models represent mental models of multiple managers involved in decision-making and that they are used as a communication tool. Models help to capture managers’ mutual impact on product performance to promote coordination and alignment of their actions (Rouwette, 2014). While the use of such models is particularly beneficial in the PLC, when some product specific data already exists, their use should not be restricted to the PLC. According to the results in Chapter 2, majority of new product introductions in European food companies are product line extensions and product improvements. Therefore, models of similar products from the same product category, which already exist in the market, can be used to develop product design and launch strategies already during NPD. Moreover, food product performance is not the only complex dynamic issue in food processing companies, and SD approach could be employed to other problems as well (e.g., production and sales planning, productivity of staff, distribution of resources, project management, etc.).

Another challenge that food companies face is a need for continuous generation of knowledge about consumers (van Kleef, 2006). As results in Chapter 2 show, European food companies frequently use consumer data in NPD, but significantly less frequently in the PLC. Scientific literature stresses the importance of understanding consumer needs and satisfying them to assure product success (Costa and Jongen, 2006; van Kleef, 2006). However, instead of collecting an abundance of data under the assumption that more data will necessarily lead to higher chances of success, food companies should develop strategies for consumer data collection, and having an SD model of product performance could potentially help. By performing sensitivity analysis on an SD model, which implies making small numerical changes in model parameters, parameters where small numerical differences lead to significant changes in product performance can be identified (Barlas, 1996). Sensitive parameters indicate that their values require precise estimations. Moreover, high leverage points need to be identified in an SD model. High leverage points of the system are areas where small actions lead to big and lasting changes (Senge, 1990). Therefore, knowing sensitive parameters and leverage points may provide guidance for consumer data collection in food processing companies. Finally, before companies decide to start collecting new consumer data, they should be aware of the data that they already possess in the company, and they should aim at understanding if they utilize the data they have to its full potential, by taking into consideration the potential of existing simulation modelling methods.

Lastly, Chapter 2 showed that European food companies rarely use complex modelling methods, such as SD and agent-based modelling. A multitude of arguments has been presented in the thesis, which display the value of studying complex dynamic problems with SD. In situations where food companies face performance issues that they cannot resolve with existing knowledge in the company, they should not hold back on seeking help from teams or individuals skilled in simulation modelling of complex issues.

9. Conclusions

In this research, we demonstrated that systems thinking and system dynamics could be applied to the complex problem of new food product performance. Firstly, the research described in this thesis showed complex interactions between variables from marketing, technology, and consumer research perspectives that affect food product performance, in the form of qualitative means-criteria diagrams. Changes in food product performance result from multiple interconnected reinforcing and balancing feedback loops. Although food companies use a variety of different methods to make product-related decisions, managers could use more objective tools to understand the impact of feedback loops on product performance. Therefore, we demonstrated that the topic of food product performance could be explored by developing quantitative system dynamics models. One such model was based on theory and empirical data from scientific literature, while another was based on stakeholders' mental models and food company data. Both of those approaches resulted with an SD model simulation, which was useful to test the impact of different strategies on product adoption in the first case, and to understand the underlying causes of unsatisfactory product sales in the second case. However, the lack of longitudinal data, and incomplete theoretical information or stakeholders' knowledge of feedback mechanisms represented a constraint in the modelling process in both cases. Nevertheless, developing an SD model resulted in an increased understanding of the feedback mechanisms influencing the product adoption and product sales. Moreover, in the second case, it positively affected cross-functional team collaboration by improving communication, insight, and shared vision of the problem. Regardless of the positive impact that SD has on understanding mechanisms that affect product performance, it is rarely employed in European food companies. In the future, more effort is required to further demonstrate the value of applying systems thinking and system dynamics in solving complex problems in food science and food industry.

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Supplementary material 1

Supplementary material to Chapter 2

1. Survey questionnaire “The use of different data types in food industry”

Introduction

Welcome to the survey about the use of different data types in food industry.

Food industry has been experiencing high failure rates of new products over the past decades. This survey aims at learning what type of data food professionals use when making decisions in different stages of food product’s life.

The survey consists of three parts:
1. General question about your work
2. Data use in new product development process (NPD)
3. Data use in product life cycle management (PLC)

It will take you up to 15 minutes to fill out the whole survey. This survey is anonymous.
We want to assure you that your responses are completely anonymous and confidential. Responses to anonymous surveys cannot be traced back to the respondent. No personally identifiable information is captured unless you voluntarily offer personal or contact information in any of the comment fields. Additionally, your responses are combined with those of many others and summarized in a report to further protect your anonymity.

Thank you for starting the survey!

PART 1. General questions about your work

1. Are you involved in new food product* development process in your company?
   *processed food products that are sold in supermarkets
   - o Yes
   - o No

2. Do you work on development of new food ingredients?
   - o Yes
   - o No

3. Do you work on development of new food ingredients?
   - o Yes
   - o No

4. Which function description fits best your job title?
   - o R&D (You design new food product recipes, which can be used as prototypes for consumer research and as test samples for (pilot) plant testing. You also work on product reformulation.)
   - o Marketing (You develop marketing strategies based on consumer and marketplace data, you prepare promotional and advertising materials and you manage the product during its product life cycle.)
   - o Consumer research (You perform research with consumers to study their response to product concepts and prototypes and/or collect information about consumers in any phase of product's life.)
   - o None of the above.

5. What is your current job title?

6. What country do you work in?

7. What is the size of the company where you work?
   - o Small (less than 50 employees)
   - o Medium (between 50 and 249 employees)
   - o Large (more than 249 employees)

8. How many years of experience in new product development jobs do you have?

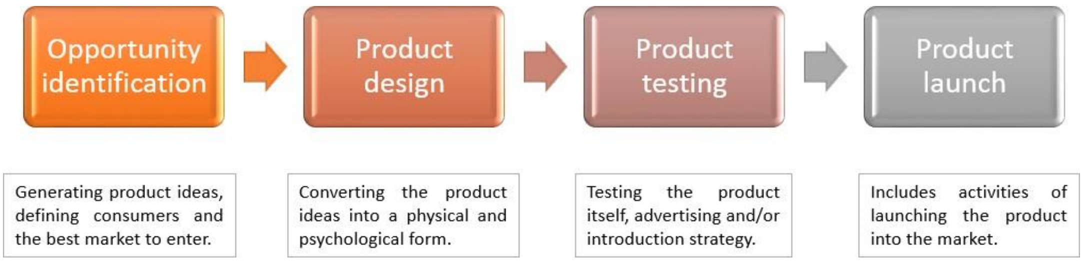
9. What group of products are you developing (for example: dairy, confectionery, meat products, cereal products etc.)?

10. Indicate how often you worked on the following types of NPD projects in the past 3 years. Please read the descriptions carefully.

	Never	Rarely	Occasionally/Sometimes	Often	Always
Product cost reductions (re-positioned as a cheaper product, with similar benefits but cheaper costs and lower price)	○	○	○	○	○
Product repositioning (products are targeted for a new use or application and usually a new market segment)	○	○	○	○	○
Product improvements (replacement of a present product with an improved version)	○	○	○	○	○
Product line extensions (additions to company's existing product lines)	○	○	○	○	○
New product lines (products are new to the company)	○	○	○	○	○
New-to-the-world (products are new to society, never seen before)	○	○	○	○	○

PART 2: Questions about data use in new product development (NPD)

Please answer questions in part 2 with new product development process (NPD) in mind. NPD typically consists of 4 phases.



11. Do you, in any way, use or collect data about consumers during NPD to make decisions about new products?
    - ○ Yes
    - ○ No

12. What consumer data collection methods have you used in NPD in the past 3 years? (more than one answer possible)

- ☐ Concept testing
- ☐ Conjoint analysis
- ☐ Consumer surveys
- ☐ Category appraisal
- ☐ Innovation templates
- ☐ Focus groups
- ☐ Consumer idealized design
- ☐ Sensory tests
- ☐ External sources (supermarkets, marketing agencies)
- ☐ Internet and magazines
- ☐ Lead-user method
- ☐ Consumer co-creation

Other (please specify)

13. In which phases of NPD do you use consumer data? (more than one answer possible)

- ☐ In opportunity identification phase
- ☐ In product design phase
- ☐ In product testing phase
- ☐ In product launch phase

14. Do you, in any way, use or collect information about food trends during NPD?
   - ○ Yes
   - ○ No

15. Indicate which trends you <u>incorporated</u> in your products in NPD during the past 3 years? (more than one answer possible)

- ☐ **Healthy food**
  (superfood, functional food, "free from" trend, clean label, sugar or calorie reduction, natural, less processed)
- ☐ **Sustainable food**
  (vegetarian, vegan, ethical, local, claim of food origin)
- ☐ **Convenience food**
  (small package units, ready-to-eat, ready-to-cook)
- ☐ None of the above

Other (please specify)

16. In what NPD phases do you use information on trends? (more than one answer possible)

- [ ] In opportunity identification phase
- [ ] In product testing phase
- [ ] In product design phase
- [ ] In product launch phase

17. How do you collect/obtain information about current food trends? (more than one answer possible)

- [ ] newsletters and reports
- [ ] consumer surveys
- [ ] scientific literature
- [ ] online databases
- [ ] internet
- [ ] food fairs
- [ ] marketing agencies, consultancy companies
- [ ] competitors' analysis

Other (please specify)

18. Indicate which of the following socio-cultural and demographic data you used in NPD in the past 3 years.

There are two columns. In each column open the drop-down menu and choose one or more data types that you have used.
If you have not used any, choose "none of the above" (you only need to choose "none of the above" once for each column).

	Socio-cultural changes in population	Demographic changes in population
1.		
2.		
3.		
4.		
5.		

Other (please specify)

19. Indicate which of the following economic and technological data you used in NPD in the past 3 years.

There are two columns. In each column open the drop-down menu and choose one or more data types that you have used.
If you have not used any, choose "none of the above" (you only need to choose "none of the above" once for each column).

	Economic changes in population	Technological changes in population
1.		
2.		
3.		
4.		

Other (please specify)

20. In what NPD phases do you use data on socio-cultural, demographic, economic and technological changes in population? (more than one answer possible)

- ☐ In opportunity identification phase
- ☐ In product design phase
- ☐ In product testing phase
- ☐ In product launch phase
- ☐ I do not use it

21. How do you collect/obtain data on socio-cultural, demographic, economic and technical changes in population? (more than one answer possible)

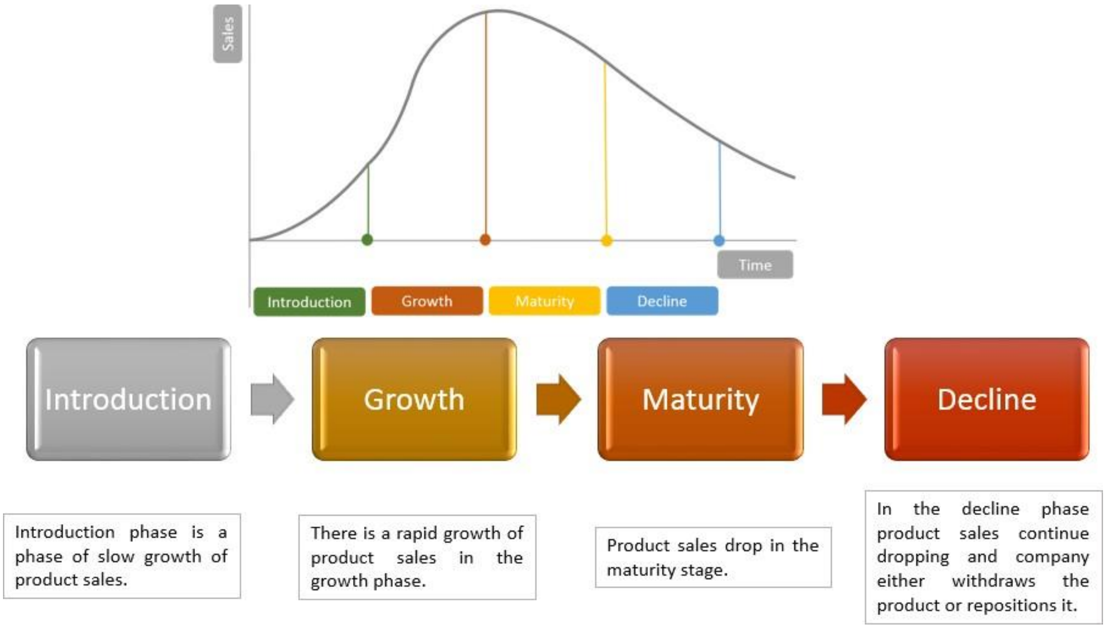
- ☐ From online databases
- ☐ From internet
- ☐ From scientific literature
- ☐ From newsletters and reports
- ☐ From marketing agencies, consultancy companies
- ☐ By undertaking surveys

Other (please specify)

PART 3: Questions about data use in product life cycle management (PLC)

In part 3 we will ask similar questions as in part 2.
Please answer the questions thinking of your products that are already on the market.

PLC typically consists of four phases.



22. Do you, in any way, use or collect data about consumers during PLC to make decisions about an existing food product?
    - Yes
    - No

23. What consumer data collection methods have you used in PLC in the past 3 years for products on the market? (more than one answer possible)

- ☐ Concept testing
- ☐ Conjoint analysis
- ☐ Consumer surveys
- ☐ Category appraisal
- ☐ Innovation templates
- ☐ Focus groups
- ☐ Consumer idealized design
- ☐ Sensory tests
- ☐ External sources (supermarkets, marketing agencies)
- ☐ Internet and magazines
- ☐ Lead-user method
- ☐ Consumer co-creation

Other (please specify)

24. In which PLC phases do you use consumer data? (more than one answer possible)

- ☐ In the introduction phase
- ☐ In the maturity phase
- ☐ In the growth phase
- ☐ In the decline phase

25. Do you, in any way, use or collect data about food trends during PLC to make decisions about existing products?
    - Yes
    - No

26. Indicate which food trends you used to change your existing products in PLC in the past 3 years. (more than one answer possible)

- ☐ **Healthy food**
  (superfood, functional food, "free from" trend, clean label, sugar or calorie reduction, natural, less processed etc.)
- ☐ **Sustainable food**
  (vegetarian, vegan, ethical, local, claim of food origin etc.)
- ☐ **Convenience food**
  (small package units, ready-to-eat, ready-to-cook etc.)
- ☐ I did not change existing products in the past 3 years

Other (please specify)

27. In which PLC phases do you use information about current food trends? (more than one answer possible)

- ☐ In the introduction phase
- ☐ In the maturity phase
- ☐ In the growth phase
- ☐ In the decline phase

28. Indicate which of the following socio-cultural and demographic data you used in PLC in the past 3 years.

There are two columns. In each column open the drop-down menu and choose one or more data types that you have used.
If you have not used any, choose "none of the above" (you only need to choose "none of the above" once for each column).

	Socio-cultural changes in population	Demographic changes in population
1.		
2.		
3.		
4.		
5.		

Other (please specify)

29. Indicate which of the following economic and technological data you used in PLC in the past 3 years.

There are two columns. In each column open the drop-down menu and choose one or more data types that you have used.
If you have not used any, choose "none of the above" (you only need to choose "none of the above" once for each column)

	Economic changes in population	Technological changes in population
1.		
2.		
3.		
4.		

Other (please specify)

30. In what PLC phases do you use data on socio-cultural, demographic, economic and technological trends in population? (more than one answer possible)

- ☐ In the introduction phase
- ☐ In the growth phase
- ☐ In the maturity phase
- ☐ In the decline phase
- ☐ I do not use it

31. Indicate which computer simulation methods you have used during NPD or PLC. (more than one answer possible)

- ☐ Agent-based modeling
- ☐ Discreet event modeling
- ☐ System dynamics modeling
- ☐ Statistical models
- ☐ I have not used computer simulation

Other (please specify)

32. Please write your e-mail address if you don't mind being contacted in case we might have more questions.

33. Please write the name of the company where you work, if you wish. (optional)

This is the end of the survey.

Thank you for participating in this survey!

To finish the survey click DONE.

If you have any questions, please contact us!

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2. "Cellwise adjusted residual method" post-hoc test

This supplementary material demonstrates how to perform a "cellwise adjusted residual method" post-hoc test of the Pearson's chi-square test of independence (MacDonald and Gardner, 2000). All statistical analyses were performed using IBM SPSS Statistics Version 23.

Firstly, Pearson's chi-square test of independence needs to be performed to examine if there is an association between the variable "size of the company" (options: small, medium, large) and the use of sensory tests (options: yes, no; variable name "method of sensory test"). Null hypothesis is that there is no association between the size of the company and the use of sensory tests.

To perform the Pearson's chi-square test of independence in IBM SPSS Statistics Version 23:

1. Analyze/Descriptive statistics/Crosstabs
2. In Crosstabs window
    a. Add the variable "size of the company" to the box "Row"
    b. Add the variable "method of sensory test" to the box "Column"
    c. Click on Statistics, and check the Chi-square box, click Continue
    d. To analyse click OK.

Figure S1.1 shows a significant result for the Pearson Chi-square test. However, a post-hoc test is needed to determine the association between a particular size of the company (small, medium, large) and the particular use of sensory tests (yes, no).

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)	Point Probability
Pearson Chi-Square	18,809[a]	2	,000	,000		
Likelihood Ratio	18,992	2	,000	,000		
Fisher's Exact Test	18,676			,000		
Linear-by-Linear Association	17,163[b]	1	,000	,000	,000	,000
N of Valid Cases	113					

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 7.40.

b. The standardized statistic is -4.143.

Figure S1.1. *Results of the Pearson's chi-square test of independence between the variable size of the company and the use of sensory tests.*

To perform the "Cellwise adjusted residual method" post-hoc test in IBM SPSS Statistics Version 23, first we need to obtain adjusted z-scores:

1. Analyze/Descriptive statistics/Crosstabs
2. In Crosstabs window
    a. Add the variable "size of the company" to the box "Row"
    b. Add the variable "method of sensory test" to the box "Column"
    c. Click on Cells, and check the Adjusted standardized residuals, click Continue
    d. To analyse click OK.

Results of adjusted standardized residuals can be seen in Figure S1.2. Adjusted standardized residuals in Figure S1.2 represent z-scores. Z-scores greater than 1.96 are statistically significant. But since we performed a series of analyses, a type 1 error could have been committed, which is why we need to calculate Bonferroni corrected p-values to determine which cells are statistically significant.

Size of the company * Method of sensory tests Crosstabulation

			Method of sensory tests		Total
			yes	no	
Size of the company	Small	Count	6,000	13,000	19
		Adjusted Residual	-2,890	2,890	
	Medium	Count	10,000	15,000	25
		Adjusted Residual	-2,447	2,447	
	Large	Count	53,000	16,000	69
		Adjusted Residual	4,300	-4,300	
Total		Count	69	44	113

Figure S1.2. *Adjusted standardized residuals of the Pearson's chi-square test of independence between the variable size of the company and the use of sensory tests. Adjusted residuals represent z-scores.*

Firstly, to determine which cells are significant, we need to obtain adjusted p-value (Bonferroni corrected p-value) to control for the type 1 error. Since we performed six analyses, we need to adjust the p-value accordingly by dividing the p-value of 0.05 with 6 (0.05/6=0.008). Our Bonferroni corrected p-value is 0.008.

Secondly, the z-scores from Figure S1.2 need to be transformed into chi-square values. First, we transfer all the z-scores from Figure S1.2 into a new column in SPSS (see adjusted_z_score column in Table S1.1). To obtain chi_square values in Table S1.1, we multiply adjusted_z_score*adjusted_z_score (in SPSS, go to Transform/Compute variable. In the

“Compute variable” window write the Target variable: chi_square. In “Numeric expression” field insert “adjusted_z_score*adjusted_z_score”. Click OK to calculate).

Thirdly, we need to obtain p-values of the chi-square values (go to Transform/Compute variable. In the “Compute variable” window write the Target variable: p_value. From “Function group” choose Significance. From “Functions and Special Variables” choose Sig.chisq. In “Numeric expression” field, the following will appear SIG.CHISQ(?). Instead of (?) insert (chi_square, 1). Number one specifies degrees of freedom. Click OK to calculate.).

Finally, compare the p_value column with the calculated Bonferroni corrected p-value (0.008). For each cell where p-value is 0.008 or lower, and where adjusted z-score is higher than 1.96, there is an association between the particular company size and the use of sensory tests. For example, there is an association between respondents from small companies and not using sensory tests (row 2 in Table S1.1).

Table S1.1. *Adjusted z-scores, chi-square values and Bonferroni corrected p-value of “Cellwise adjusted residual method” post-hoc test for the size of the company and the use of sensory tests.*

	adjusted_z_score	chi_square	p_value
1	-2,890	8,352	,004
2	2,890	8,352	,004
3	-2,450	6,003	,014
4	2,450	6,003	,014
5	4,300	18,490	,000
6	-4,300	18,490	,000

Reference:

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Supplementary material 2

Supplementary material to Chapter 3

1. Literature review strategy to find relevant studies

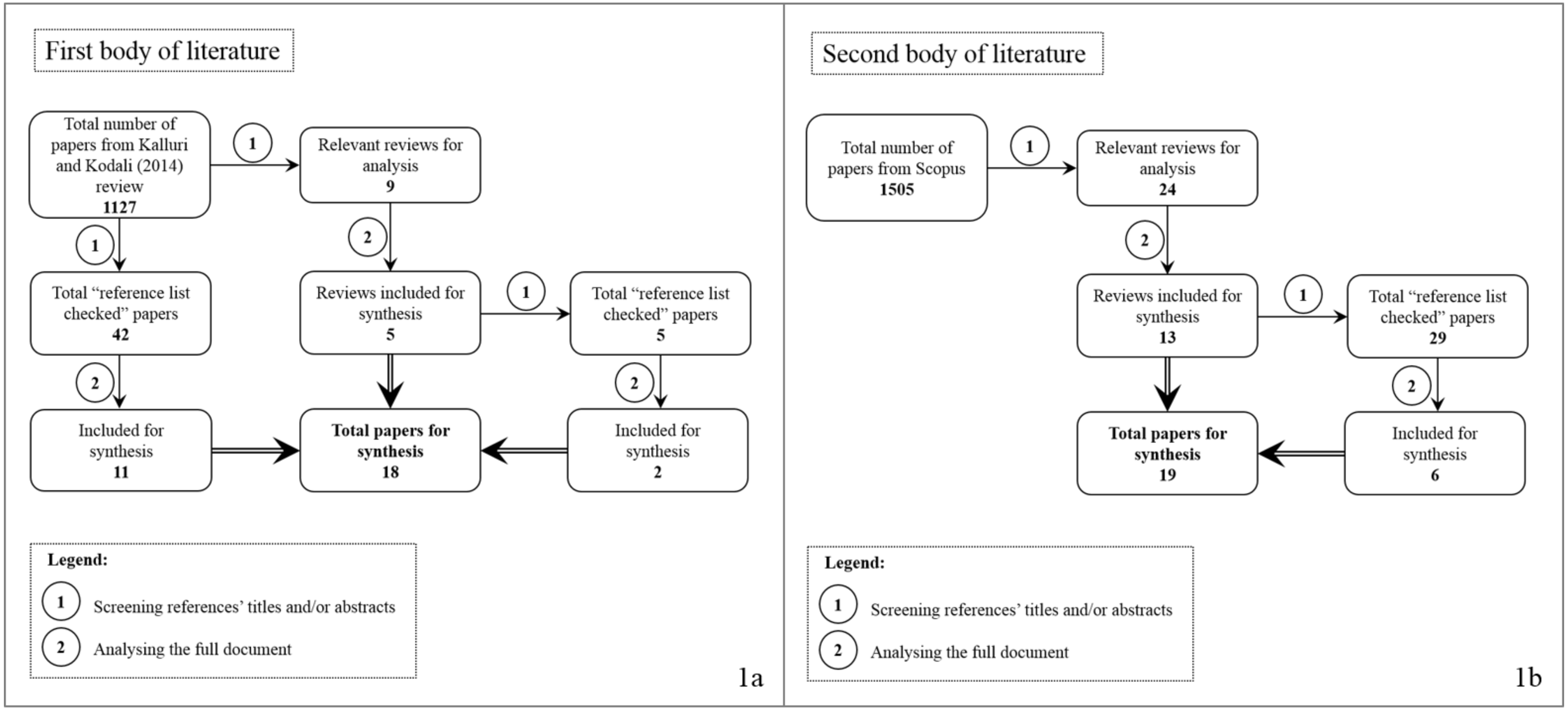

Figure S2.1: *Diagram showing the process of finding relevant studies; [a] the first body of literature; [b] the second body of literature.*

2. Articles used for data synthesis

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Supplementary material 3

Supplementary material to Chapter 4

1. Data used to formulate variables of the insect-based food adoption model

Table S3.1: *Data used to formulate variables of the insect-based food adoption model*

Variable	Definition	Data used from the source(s)	Source*
average appropriateness	Average appropriateness of insect-based food of the total population; based on average familiarity of the population with insect-based food	Evaluation of expected appropriateness within three familiarity levels: Tasted before: 6.5/9 Known as food, never tasted:6/9 Not known as food:3.2/9	Based on Figure 2 from Tan et al., (2016)
average taste expectation	Average taste expectation of insect-based food of the total population; based on average familiarity of the population with insect-based food	Evaluation of taste expectation within three familiarity levels: Tasted before: 5.2/9 Known as food, never tasted:4/9 Not known as food:2.5/9	Based on Figure 2 from Tan et al., (2016)
barrier towards tasting	Barrier towards tasting insect-based food as a result of average disgust levels of the population	Tan et al. (2016): 98.97% participants tasted a mealworm burger. Schouteten et al., (2016): 88.68% of the study participants did not want to try an insect-based burger.	Based on Schouteten et al. (2016), and Tan et al. (2016)
likelihood to adopt insect-based food	Likelihood to adopt insect-based food as a result of the barrier towards adopting	Verbeke (2015): 19.3% ready to adopt insects as a meat substitute . Vanhonacker et al. (2013): 5% consumers ready to adopt.	Based on Vanhonacker et al., (2013), and Verbeke (2015)
availability	Variable that represents availability of insect-based burgers in the Netherlands, with value 0 before year 2015 and value 1 from year 2015	Evidence of insect-based burgers being present on the Dutch market in 2015.	Based on Glover and Sexton (2015)
average disgust level	The average level of disgust of the population when in the situation of tasting insect-based food, from 0 (no disgust, 100% chances of tasting) to 1 (100% disgust, 0% chances of trying)	32% of participants mentioned disgust as an emotion related to insect-based burgers.	Based on Table 3 from Schouteten et al. (2016)

average sensory quality of insect-based burger	Average sensory liking of an insect-based burger and insect-based meatballs	Tan et al. (2016): Average sensory liking: 6/9. Schouteten et al. (2016): Average sensory liking: 4.2/9	Based on Schouteten et al. (2016), and Tan et al., (2016)
fraction of potential tasters from promotional activities	Fraction of potential adopters exposed to promotional activities of insect-based food	Calibrated for the model to reach average familiarity of approximately 22% by 2015 (Tan et al., 2016) and for cumulative internal influence (number of "Potential tasters" in the end of the simulation as a result of word-of-mouth) to be approximately ten times bigger than cumulative external influence (number of "Potential tasters" in the end of the simulation from promotional activities)(Goldenberg and Shapira, 2009).	Assumption based on Goldenberg and Shapira (2009), and Tan et al. (2016)
strength of the word-of-mouth	Probability that the contact with Potential adopters will result with fruitful word-of-mouth	Calibrated for the model to reach average familiarity of approximately 22% by 2015 (Tan et al., 2016) and for cumulative internal influence (number of "Potential tasters" in the end of the simulation as a result of word-of-mouth) to be approximately ten times bigger than cumulative external influence (number of "Potential tasters" in the end of the simulation from promotional activities)(Goldenberg and Shapira, 2009).	Assumption based on Goldenberg and Shapira (2009), and Tan et al., (2016)
Total population	Total model population representing people in the Netherlands expected to have meat eating diets	CBS StatLine (2017): Total population of the Netherlands in the year 2015 was 16900720. Dagevos et al. (2012) and van Rossum et al., (2016): 4% of the population with special eating habits (e.g. vegetarian, vegan, macrobiotic, anthroposophical).	Based on CBS StatLine (2017), Dagevos et al. (2012), and van Rossum et al. (2016)

*For references see Chapter 4

Structure oriented behaviour tests of model validation

Structure oriented behaviour tests, with the purpose of model validation, included sensitivity analysis and extreme conditions tests (Pruyt, 2013; Sterman, 2004; Barlas 1994). This supplementary material contains examples of the two performed tests.

1.1. Sensitivity analysis

Sensitivity analysis includes studying the effect of small changes in parameters on model behaviour in order to look for model errors, to understand the relationships between inputs and emergent behaviour, and to identify highly sensitive inputs (Pruyt, 2013; Barlas, 1996). The aim is to understand if performed changes lead to, for example, behaviour sensitivity (changes in modes of behaviour), or to mere numerical sensitivity, and to what extent (Pruyt, 2013). This helps with establishing an order of preference in policies, or pinpoints to sensitive variables that need to receive greater attention when estimating the values and formulas.

We studied the effect of 10% change in constant variables. All simulations were performed with Sensitivity Control feature of Vensim DSS, Version 6.4b (2018). The following settings were employed: multivariate sensitivity simulations (allows for Monte Carlo simulations); number of simulations: 1000; noise seed: 1234; distribution: random uniform; minimum value: base run parameter value-10%*base run parameter value; maximum value: base run parameter value+10%*base run parameter value.

We will demonstrate the results of sensitivity analysis for two variables, to display different sensitivity levels, i.e. “fraction of potential tasters from promotional activities” and “average sensory quality of insect-based burger”. Table S3.1 shows the variable values used for the sensitivity analysis. Sensitivity analysis was performed separately for each variable. The same approach has been used for all the other constant variables in the model.

Table S3.1. *Minimum and maximum values of variables used for sensitivity analysis*

Variable	Base run value (Dmnl)	Minimum value (Dmnl)	Maximum value (Dmnl)
fraction of potential tasters from promotional activities	0.0036	0.00324	0.00396
average sensory quality of insect-based burger	0.54	0.486	0.594

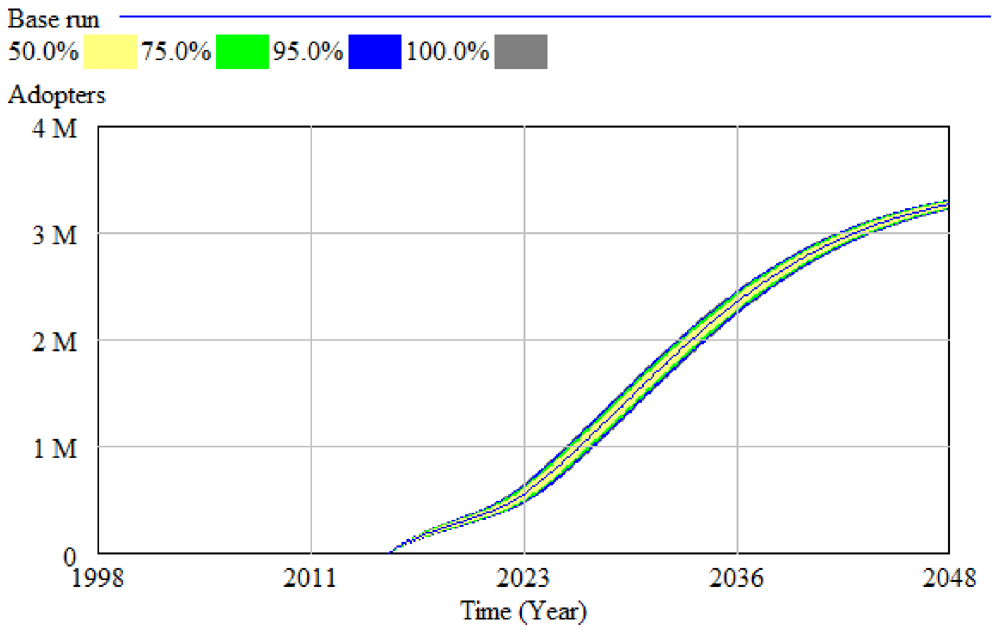

Figure S3.1. *Results of the sensitivity analysis of the variable "fraction of potential tasters from promotional activities".*

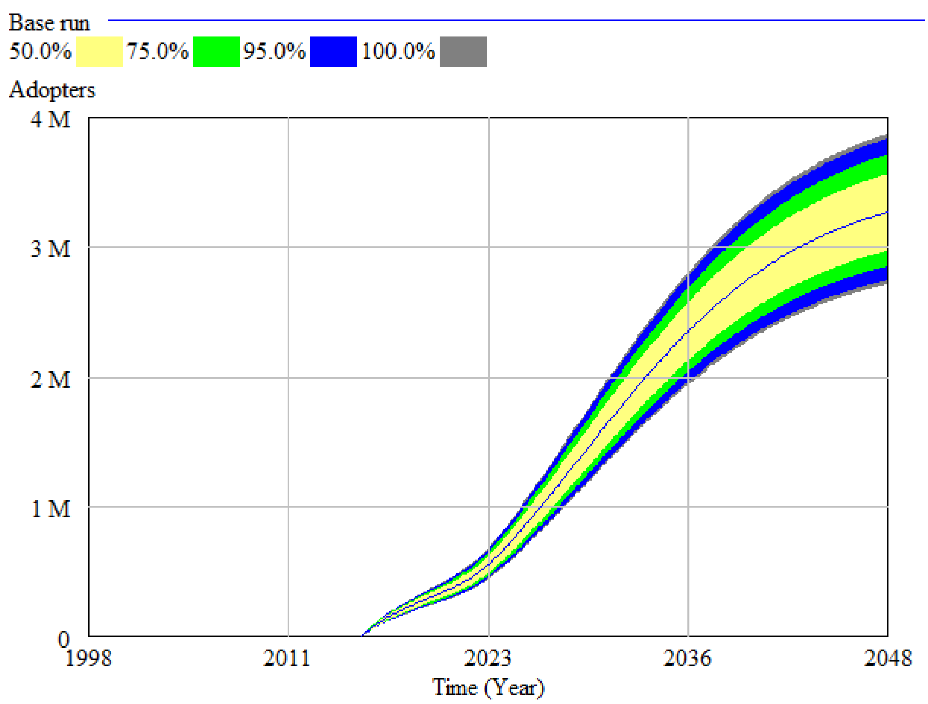

Figure S3.2. *Results of the sensitivity analysis of the variable "average sensory quality of insect-based burger".*

Results of the sensitivity analysis in Figure S3.1 and Figure S3.2 are shown as graphs with confidence bounds. Graphs are assessed qualitatively, by asking if the real system would be similarly sensitive to the tested parameters. One aims at determining the parameters to which the model is highly sensitive (Barlas, 1996). Figures S3.1 and S3.2 show that the behaviour of the stock "Adopters" is not strongly sensitive to the variable "fraction of potential adopters from promotional activities", while the variable "average sensory quality of insect-based burger" is numerically sensitive. Although the aim of the modelling process is not to predict the outcome of the diffusion process, but to study the effect of changes on model behaviour, the outcome of sensitivity analysis may have implications for future data collection. To have more confidence in the results, one would need to assess sensory quality variable with more precision than the other tested variable. Furthermore, Figure S3.2 suggests that both variables do not express behaviour sensitivity, as they both show S-shaped growth. This implies that the model behaviour results from the model structure, and not from the uncertainty of the variables.

1.2. Extreme conditions test

Extreme conditions test includes evaluation of model equations under extreme conditions (Barlas, 1994). It is performed by assigning extreme values to input variables to assess if the model responds plausibly. The aim is to test if the model conforms to the basic physical laws (e.g., if there is no product available, there will be no adopters) (Sterman, 2004). Although we here give only one example, this test has been performed on other input variables in the same manner.

We will demonstrate an example of extreme conditions test on the variable "fraction of potential tasters from promotional activities". To assess if the model responds appropriately to extreme values, we assigned value zero to the variable "fraction of potential tasters from promotional activities", assuming a situation where there is no external influence to seed the system with tasters who can start spreading word-of-mouth. Figure S3.3 shows that the model passed the extreme conditions test since there are no adopters.

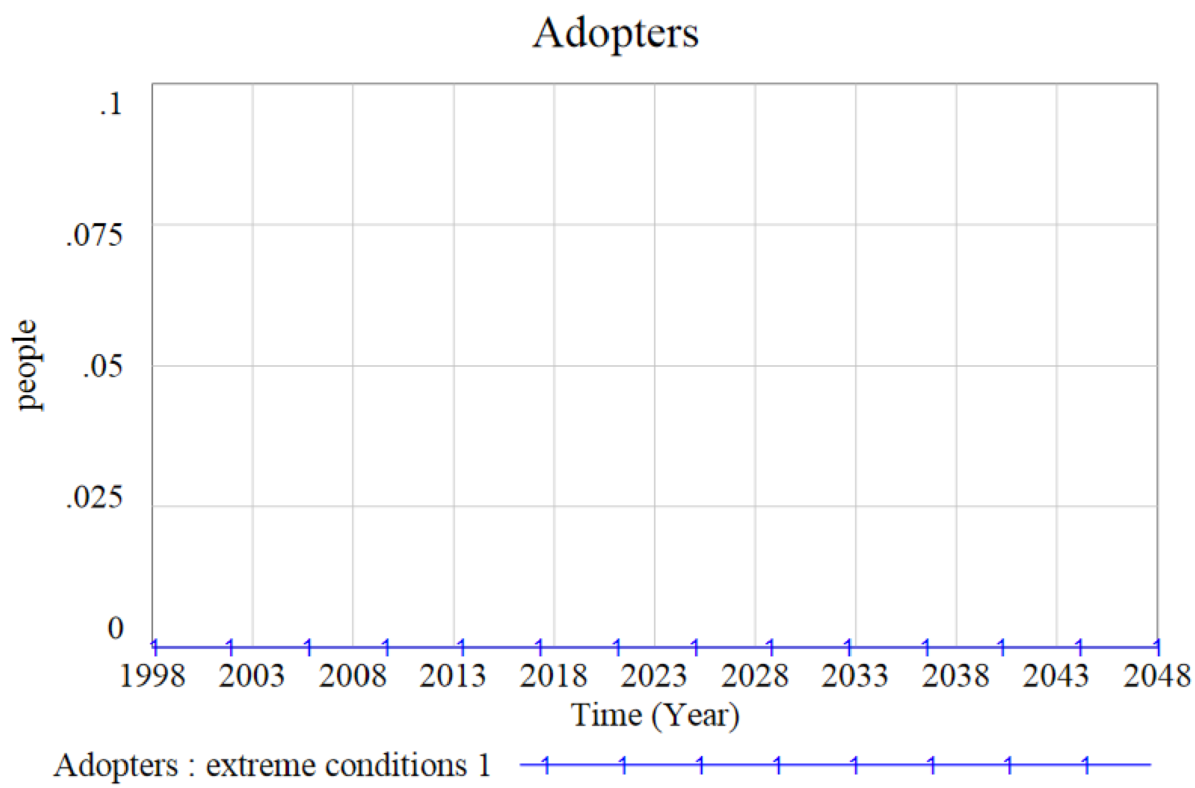

Figure S3.3. *Result of extreme conditions test for variable "fraction of potential tasters from promotional activities".*

References

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Supplementary material 4

Supplementary material to Chapter 5

1. Detailed agenda of group model building (GMB) sessions

Table S4.1. *Agenda of the 1st GMB session (the 26th of March, 2018)*

Time	*Activity*
14.00-14.10	Welcome and introduction
14.10-14.35	Hopes and fears
14.35-15.05	Key stakeholders elicitation
15.05-15.35	Strategy elicitation
15.35-15.50	Break
15.50-16.05	Concept model presentation
16.05-17.05	Graphs over time exercise
17.05-17.15	Next steps and closing

Table S4.2. *Agenda of the 2nd GMB session (the 28th of March, 2018)*

Time	*Activity*
13.45-14.00	Review of the 1st session
14.00-15.10	Model structure elicitation
15.10-15.20	Break
15.20-16.25	Model structure elicitation
16.25-16.35	Break
16.35-16.50	Model review
16.50-17.00	Next steps and closing

Table S4.3. *Agenda of the 3rd GMB session (the 24th of May, 2018)*

Time	*Activity*
10.30-10.35	Welcome and review of the 1st and the 2nd session
10.35-10.40	Presentation of the current model
10.40-11.50	What-if exercise
11.50-12.00	Break
12.00-13.00	Consumer buying behaviour – group discussion
13.00-14.00	Lunch break
14.00-14.45	Consumer buying behaviour – continuation
14.45-15.40	Break
14.45-15.40	Nonlinear graphs exercise
15.40-16.00	Parameter elicitation exercise
16.00-16.15	Next steps and closing

Table S4.4. *Agenda of the 4th GMB session (the 22nd of November, 2018)*

Time	*Activity*
13:00-13.20	Welcome and review of the past sessions
13.20-14.20	Presentation of simulated scenarios
14.20-14.30	Break
14.30-15.15	Exercises – participants use the model interface
15.15-15.30	Closing the session
15.30-15.45	Post-test survey

2. "Concept model" script (based on Hovmand et al., 2013)

The facilitator explains the symbolism and the principles of system dynamics models, while simultaneously drawing the model. The modeller assists by showing the behaviour of the projected model.

2.1. Explaining stocks, flows and feedback loops

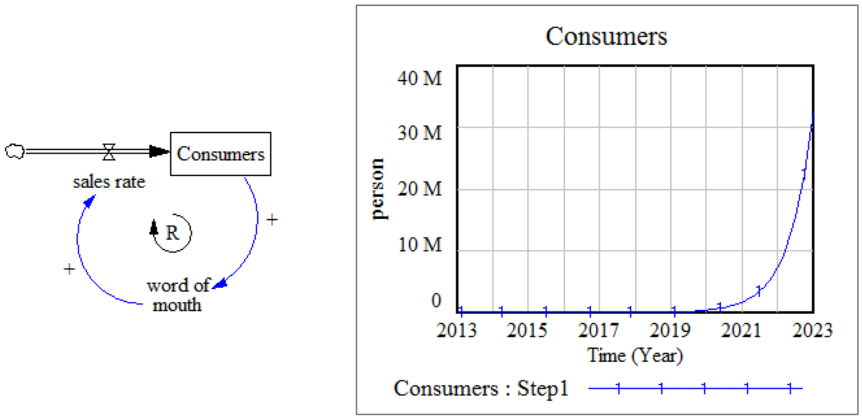


Figure S4.1. *Concept model used to explain stocks, flows, reinforcing feedback loops, and the behaviour of a single reinforcing feedback loop.*

2.1.1. Explaining stocks and flows

The facilitator asks the participants to imagine that all of the consumers of a certain product are in one box called a stock (the facilitator draws a stock of "Consumers" on a whiteboard). A stock is like a bathtub (the facilitator draws a bathtub with water, close to the SFD that will be drawn). If you want to increase the level of water in the bathtub, you need to have a flow of water coming into the bathtub. Similarly, if you want to increase the number of consumers, you need to sell more products. The more products you sell, the more consumers you will have in the stock (The facilitator draws the flow "sales rate" in the SFD, and a pipe going to the bathtub, representing the flow of water).

2.1.2. Explaining reinforcing feedback loops

If consumers are satisfied with the product, they might talk to people who haven't tried it about their experience. This is called word-of-mouth (facilitator draws the variable "word-of-mouth" and an arrow from the "Consumers" stock to the "word-of-mouth" variable). The people who consumers talk to might want to buy the product, which might increase the sales rate (facilitator draws and arrow from "word of mouth" variable to "sales rate" flow). We draw the causal influence of one variable on another with an arrow. If there is a sign +, it means variables move in the same direction. For example, the more consumers we have, the more word-of-mouth there is. Or the less consumers we have, the less word-of-mouth there is. If there would be a sign -, it means variables move in the opposite direction. For example, the more consumers we have, the less word-of-mouth there is. Or the less consumers we have, the more word-of-mouth there is. But this last situation is not true here, and that is why we have a + sign.

If we now move forward, we can conclude that the more word-of-mouth there is, the higher sales rate becomes. Or, if there is less word-of-mouth, the sales rate will be lower and there will be less consumers in the stock. This is called a reinforcing feedback loop (facilitator draws a sign for a reinforcing feedback loop. Interestingly, we can model and simulate this on a computer.

The modeller turns on the projector and shows the same model, which the facilitator drew, in Vensim. He/she runs that model and shows the behaviour of the "Consumers" stock. The facilitator explains that on the x-axis is time, and on the y-axis is the stock of consumers. The number of consumers increases over time. The facilitator points out that in this situation the reinforcing feedback loop makes the value of the stock to increase.

2.1.3. Explaining balancing feedback loops

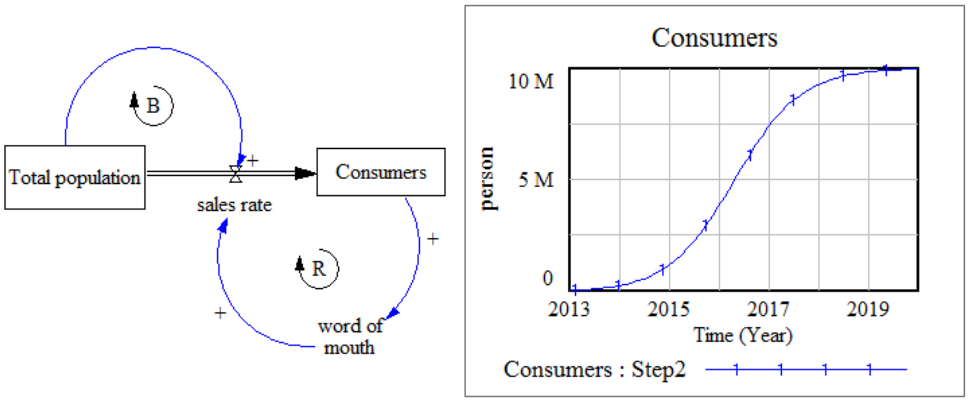


Figure S4.2. *Concept model that explains the behaviour of a single reinforcing and a single balancing feedback loop.*

In the next step, facilitator points out that the behaviour of the model (in Figure S4.1) is unrealistic since the market where the product is launched only has 10 million people, while the model shows 30 million consumers. That means that something that is stopping the sales rate from growing that much exists, which also means that the model is not complete. For the beginning, there should be another stock which represents the Total population on the market (facilitator draws the stock of "Total population"). Now the "sales rate" can grow only until there are people in the stock of "Total population". Facilitator points out that participants can think of this stock as a tank of water (facilitator draws a water tank and connects it to the pipe in the image with the bathtub). In the beginning, there is a lot of water in the tank, but as the water flows, the tank will get empty. Similarly, as the stock of "Total population" empties, there will be no "sales rate" and no new consumers (facilitator draws an arrow from the stock of "Total population" to "sales rate"). This is called a balancing feedback loop (Figure S4.2). It shows that something is limiting the growth, something is constraining sales from growing, from increasing the "sales rate", and in this case it is the number of "Total population" on the market. We can once again show that on the projector and run it (the modeller turns on the projector and shows the model with the new structure and the behaviour of the stock "Consumers"). Facilitator points out that the model behaviour has changed, and the curve now shows an S-shaped growth. This is because there is one reinforcing feedback loop, which is making the "sales rate" grow when there is a lot of people in the "Total population" stock, and one balancing feedback loop, which is stopping the “sales rate” from growing, once the “Total population” stock starts emptying.

The facilitator ends the story by pointing out that system dynamics models usually contain variables and feedback loops that are pushing the growth, and variables and feedback loops that are restraining the growth. Finally, the facilitator explains what the group just learned: the symbols, which will be used in the sessions; that the diagrams can be quantified and simulated; that the structure of the model affects how the model behaves; and that the models can be repeatedly refined.

3. Seed structure for the “Causal mapping with the seed structure” script (Hovmand et al., 2013)

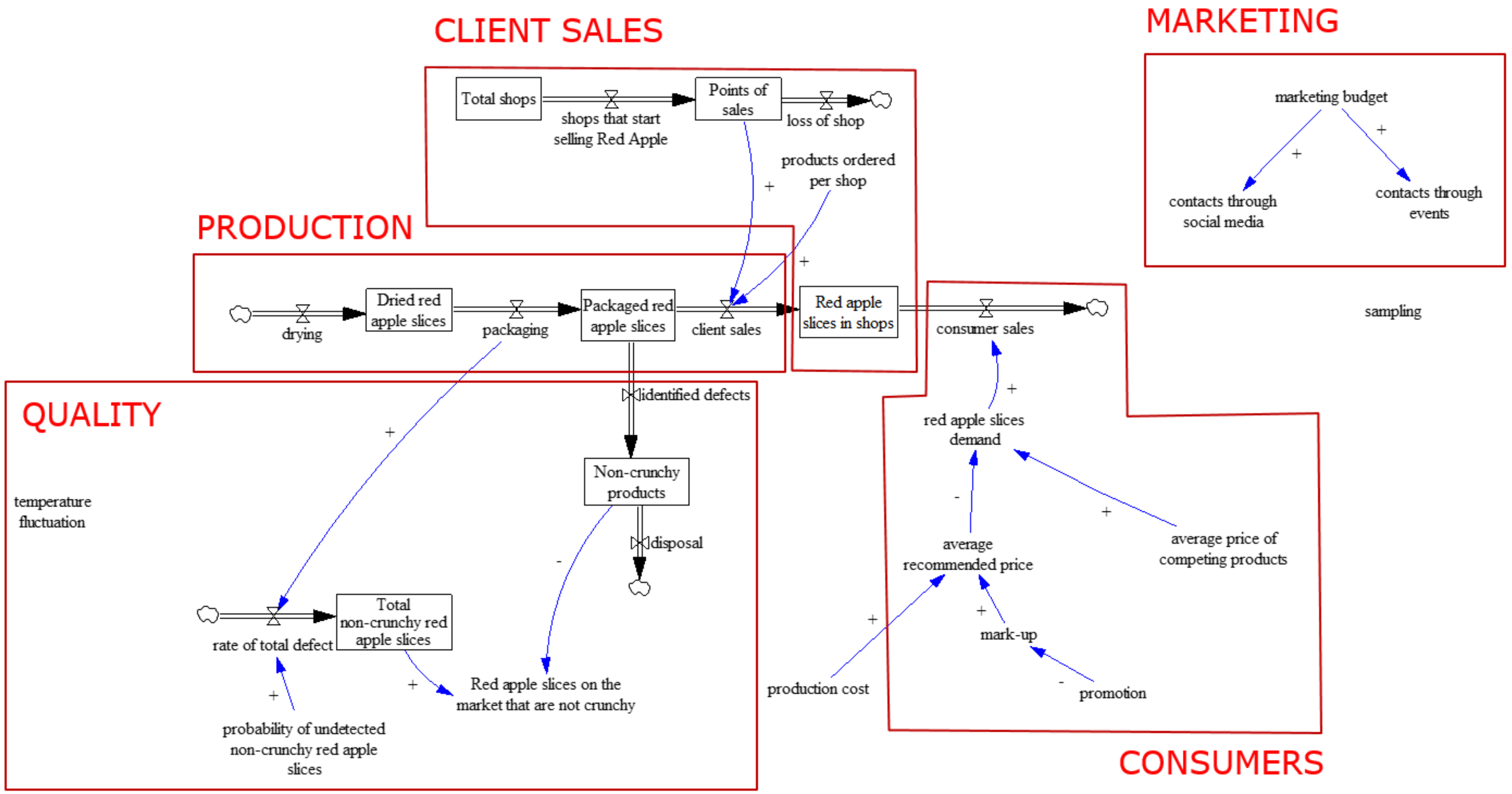


Figure S4.3. *A Seed structure for starting the structure elicitation of the stock and flow diagram. The red squares represent different sectors of the diagram, which were used to explain the diagram to the participants.*

4. CICC Questionnaire (Rouwette, 2011)

Dear participant,

This questionnaire evaluates the use of Group Model Building in understanding why the sales of your product have been stagnating or not growing as expected.

This questionnaire addresses the urgency of the problem at stake, results of the modelling sessions, the effects of different aspects of the sessions, quality of the modelling process, and suggestions for future sessions. We politely invite you to answer these questions as best as you can. The results of this questionnaire will be used to improve the procedure that was used.

Before addressing the sessions, we would like to ask for some background information. All information will be treated confidentially.

I am a member of this firm since ....

My function in this firm is ....

Thank you for your cooperation.

Results of the modelling process

The following questions aim primarily at the discussions that were held while making the causal models. These questions also refer to the results of the analysis of data and simulations. The answers on the following questions fall in one of the five categories:

Strongly agree	(sa)
Agree	(a)
Neither agree nor disagree	(a/d)
Disagree	(d)
Strongly disagree	(sd)

	sa	a	a/d	d	sd
1. My insight into the problem has increased due to the modelling process.					
2. I think that, because of these meetings, we have reached a shared vision of the problem.					
3. I support the conclusions/findings that were drawn during the modelling process.					
4. The modelling process has given me more insight into the cohesion between the elements that compose the problem.					
5. The causal diagrams that were developed were the result of the integration of diverse opinions and ideas of participants.					
6. If I were to use the same approach again with people from my firm, in planning and in dealing with other problems, all persons would loyally follow this plan to its natural conclusion.					
7. As a result of the modelling process, it is still *unclear* to me what the causes of the problem, that play behind the scenes, are.					
8. The modelling process aided in the understanding of the opinions of other participants.					
9. We could *not* reach a consensus (a general agreement).					
10. The use of causal diagrams has clarified the communication between participants about the problem.					
11. Our opinions are closer due to the modelling process.					
12. I will support the conclusions/findings of these meetings in front of other members of my organisation.					
13. The modelling process has given me more insight into the feedback processes that play a role in the problem.					
14. The modelling process has given me *little* insight into the feedback processes that play a role in the problem.					
15. Some persons dominated the discussion.					
16. The modelling process has *not* given me insight into the possibilities that my organisation has in “steering” the problem.					
17. I will try to convince others in my organisation of the importance of these conclusions.					
18. Using modelling in approaching the problem is efficient.					
19. All in all, I think these meetings were successful.					

If you compare these meetings, where causal diagrams were used, with normal meetings in which you discuss similar problems, would you say these meetings:

	sa	a	a/d	d	sd
generate *more* insight compared to normal meetings?					
generate insight *more quickly* compared to normal meetings?					
result in a *better* communication between participants?					
generate a shared vision between participants *more quickly*?					
generate a *better* shared vision between participants?					
generate commitment of participants *more quickly*?					
generate *more* commitment of participants?					

Effects of different elements of Group Model Building

The meetings consisted of several aspects, which may have contributed in different ways to the overall effect of the meetings. In the following questions you are asked to specify how much has an aspect contributed to the overall effect. You can do this by scoring each element on a scale of -5 to +5, in which

-5 = was of no use whatsoever, obstructed the sessions;

0 = did not obstruct, but was of no use either;

+5 = contributed very much

	score -5 to 5
The fact that the diagrams were projected in a way that was visible to everybody.	
The fact that an outsider was accompanying as a “group facilitator”.	
The opportunity for open and extensive discussion.	
The use of causal diagrams.	
Gathering the data needed for the quantitative model.	
Analysing the data.	
Simulation, using the quantitative model.	
Other:	

Quality of the Group Model Building project

The following questions aim at the quality of the modelling process. By "problem" we refer to the problem definition that was used in the modeling process: understanding why the sales of your product have been stagnating or not growing as expected.

The answers on the following questions fall in one of the five categories:

Strongly agree	(sa)
Agree	(a)
Neither agree nor disagree	(a/d)
Disagree	(d)
Strongly disagree	(sd)

	sa	a	a/d	d	sd
The current situation of my organisation was well mapped.					
The description of the situation to be reached was correct.					
In the modelling process the right definition of the problem was used.					
In the modelling process all relevant information was used.					
The analysis of the information was correct.					
All issues or problem areas that needed attention were investigated.					
In the modelling process *not* all useful solutions were discussed.					
In the modelling process the positive and negative sides of possible solutions were attended to.					
The choice of the most promising solution was based on sound arguments.					
In the modelling process the best solution was chosen.					

Suggestions for future sessions

The following answers can be of great use in planning future sessions.

What were the three best features of the sessions?

1. ______________________________
   ____

2. ______________________________
   ____

3. ______________________________
   ____

What were the three most disappointing features or problems of the sessions?

1. ______________________________
   ____

2. ______________________________
   ____

3. ______________________________
   ____

What specific suggestions would you make if meetings like these were to be organised or held again?

1. ______________________________
   ____

2. ______________________________
   ____

3. ______________________________
   ____

Thank you again for your cooperation.

5. Stock and flow diagram with formulations of the variables in Vensim

This supplementary material contains the following information:

- A complete stock and flow diagram of the partial model structer presented in Figure 5.6 of the manuscript;
- Vensim formulations of the variables in the stock and flow diagram.

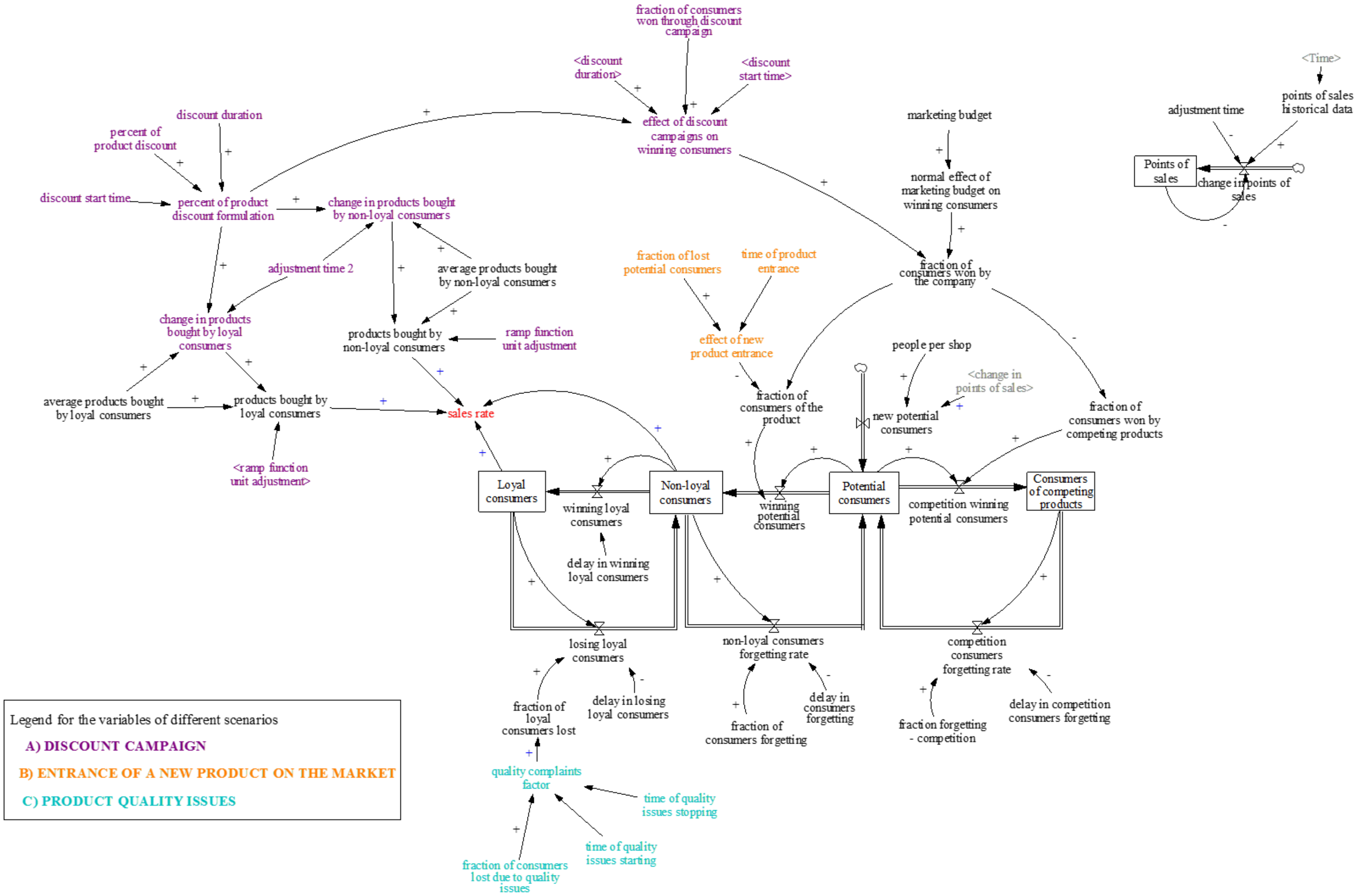


Figure S4.4. *Complete stock and flow diagram of the partial model structer presented in Figure 5.6 of the manuscript.*

Table S4.5. *Formulations of the variables of the Vensim model* in Figure S4.4*

Variable name	Unit	Formulation
adjustment time	Month	= 0.125
adjustment time 2	Month	= 0.125
average products bought by loyal consumers	units/(people*Month)	= 5.4022
"average products bought by non-loyal consumers"	units/(people*Month)	= 0.2
change in points of sales	shop/Month	= (points of sales historical data-Points of sales)/adjustment time
change in products bought by loyal consumers	units/(people*Month)	= SMOOTH(percent of product discount formulation*average products bought by loyal consumers, adjustment time 2)
"change in products bought by non-loyal consumers"	units/(people*Month)	= SMOOTH("average products bought by non-loyal consumers"*percent of product discount formulation, adjustment time 2)
competition consumers forgetting rate	people/Month	= DELAY1(Consumers of competing products*"fraction forgetting - competition", delay in competition consumers forgetting)
competition winning potential consumers	people/Month	= Potential consumers*fraction of consumers won by competing products
Consumers of competing products	people	= ∫ competition winning potential consumers-competition consumers forgetting rate *dt* + [0]
delay in competition consumers forgetting	Month	= 3.35447
delay in consumers forgetting	Month	= 14.7435
delay in losing loyal consumers	Month	= 5.48336
delay in winning loyal consumers	Month	= 21.0381
discount duration	Month	= 0
discount start time	Month	= 72
effect of discount campaigns on winning consumers	1/Month	= percent of product discount formulation*fraction of consumers won through discount campaign*PULSE(discount start time, discount duration)
effect of new product entrance	Dmnl	= 0.96-STEP(0.56, 12)-STEP(0.09, 24)-STEP(0.01, 36) +STEP(0.02, 48)-STEP(0.06, 60)-STEP(fraction of lost potential consumers, time of product entrance)
"fraction forgetting - competition"	1/Month	= 0.122912
fraction of consumers forgetting	1/Month	= 0.5
fraction of consumers lost due to quality issues	1/Month	= 0
fraction of consumers of the product	1/Month	= fraction of consumers won by the company*effect of new product entrance
fraction of consumers won by competing products	1/Month	= 1-fraction of consumers won by the company
fraction of consumers won by the company	1/Month	= normal effect of marketing budget on winning consumers + effect of discount campaigns on winning consumers
fraction of consumers won through discount campaign	1/Month	= 0
fraction of lost potential consumers	Dmnl	= 0

fraction of loyal consumers lost	1/Month	= 0.104905+quality complaints factor
losing loyal consumers	people/Month	= DELAY1(Loyal consumers*fraction of loyal consumers lost, delay in losing loyal consumers)
Loyal consumers	people	= ∫ winning loyal consumers-losing loyal consumers *dt* + [0]
marketing budget	euro	= 120000-STEP(10000, 12)+STEP(10000, 24)+STEP(10000, 36)-STEP(40000, 48)+STEP(40000, 60)
new potential consumers	people/Month	= people per shop*change in points of sales
"Non-loyal consumers"	people	= ∫ winning potential consumers + losing loyal consumers-winning loyal consumers-"non-loyal consumers forgetting rate" *dt* + [0]
"non-loyal consumers forgetting rate"	people/Month	= DELAY1(fraction of consumers forgetting*"Non-loyal consumers", delay in consumers forgetting)
normal effect of marketing budget on winning consumers	1/Month	= WITH LOOKUP (marketing budget, ([(0, 0)-(1e+006, 10)], (0, 0.1), (90000, 0.6), (130000, 0.65), (250000,0 .72),(500000, 0.8), (1e+006, 0.9)))
people per shop	people/shop	= 10.4848
percent of product discount	Dmnl	= 0
percent of product discount formulation	Dmnl	= percent of product discount*PULSE(discount start time , discount duration)
Points of sales	shop	= ∫ change in points of sales *dt* + [600]
points of sales historical data	shop	= WITH LOOKUP (Time, ([(0, 0)-(96, 20000)], (0, 0), (5.9, 600), (12, 4825), (24, 6857), (36, 12676), (48, 12863), (60, 15309), (72, 15755), (84, 16055), (96, 16355), (108, 16355)))
Potential consumers	people	= ∫ competition consumers forgetting rate + "non-loyal consumers forgetting rate" + new potential consumers-competition winning potential consumers-winning potential consumers *dt* + [0]
products bought by loyal consumers	units/(people*Month)	= average products bought by loyal consumers+ RAMP(change in products bought by loyal consumers/ramp function adjustment, 0, 0)
"products bought by non-loyal consumers"	units/(people*Month)	= "average products bought by non-loyal consumers" + RAMP ("change in products bought by non-loyal consumers"/ramp function adjustment, 0, 0)
quality complaints factor	1/Month	= STEP(fraction of consumers lost due to quality issues, time of quality issues starting)-STEP(fraction of consumers lost due to quality issues, time of quality issues stopping)
ramp function adjustment	Month	= 24
time of product entrance	Month	= 0
time of quality issues starting	Month	= 0
time of quality issues stopping	Month	= 0
winning loyal consumers	people/Month	= “Non-loyal consumers"/delay in winning loyal consumers
winning potential consumers	people/Month	= Potential consumers*fraction of consumers of the product

*time step: 0.0078125, integration: RK4 Auto, initial time: 6, final time: 108, units for time: Month

6. Calibration of the unknown model parameters

The model was calibrated with the Optimizer function in Vensim DSS. The model structure presented in Figure S4.4 of this supplementary material was calibrated to the data of actual sales (Figure 5.2 in Chapter 5).

We used the following Optimizer settings:

Optimizer: Powell
Random type: Default
Output level: On
Trace: Off
Vector points: 25
Max iterations: 1000
Stochastic: No
Pass Limit: 2
Frac Tol: 0.0003
ABS Tol: 1
Scale ABS: 1
Sensitivity: Off
Multiple Start: Off
Tol Mult: 21

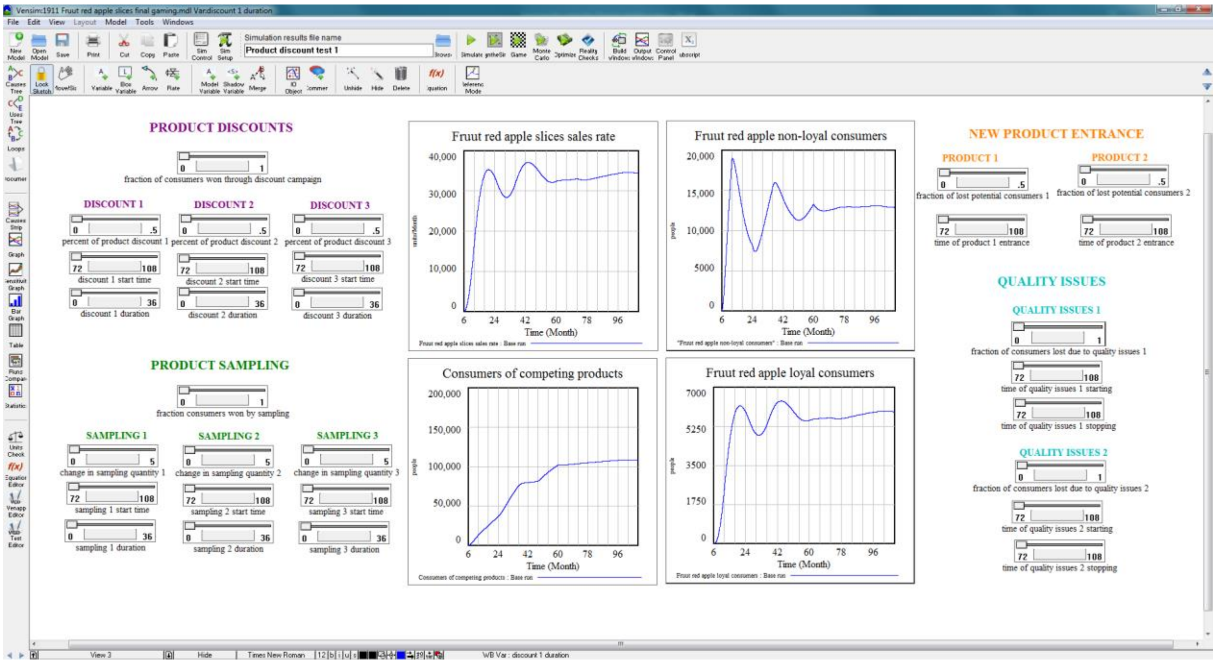
Parameters calibrated (and value ranges):

Average number of products bought by loyal consumers (1-10)
Average number of products bought by non-loyal consumers (0.2-5)
Delay in competition consumers forgetting (0-6)
Delay in losing loyal consumers (1-48)
Delay in winning loyal consumers (1-50)
Fraction forgetting – competition (0.01-1)
Fraction of consumers forgetting (0.01-1)
Fraction of loyal consumers lost (0.01-1)
People per shop (1-100)
Delay in consumers forgetting (0-18)

7. Exercises for participants of the group model building session 4 for using the Vensim model interface

Please open the Vensim model of the sales of healthy fruit snack.

After opening the model, the interface below appears.



This will be the interface that you will use to perform different model tests with.

There are 4 graphs, which all show a base run in the beginning. Base run represents the run when no changes to the model parameters have been made (when you have not been moving any sliders). One graph shows the behaviour of the variable sales rate (in units of "product sold per month" on the x-axis) and other graphs show the 3 main stocks of the model. The model time is in months (on the y-axis). The space between two vertical lines corresponds to 6 months. The model runs from the beginning of July 2013 (time 6), until the end of December 2021 (time 108). However, the model tests that you can execute are only possible from time 72, which corresponds to the beginning of January 2019. This is because we assume that you cannot change the past, but only the future. Unfortunately, since we are using the free version, the time cannot be displayed in dates.

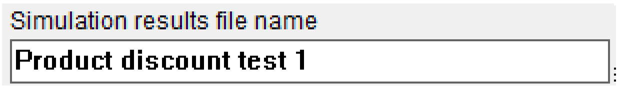
On the left and the right sides are sliders. Each slider allows you to change a numerical value of one model parameter by moving it.

Exercise 1: Product price discount

In this exercise, you will be changing the parameters related to product discounts. Your task is to produce the behaviour from the slides that were presented earlier today.

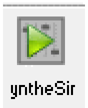
1. Before running a test, you need to give your test a name.

Click in the field (see below)



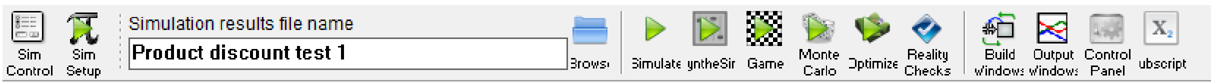
and give your run a name. For example "Product discount test 1".

2. Now click on the button SyntheSym (see below), situated on the right side from the field where you changed the name.

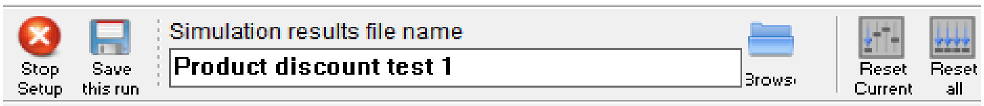


The appearance of the interface will change once you click on SyntheSim.

The appearance before clicking on SyntheSym

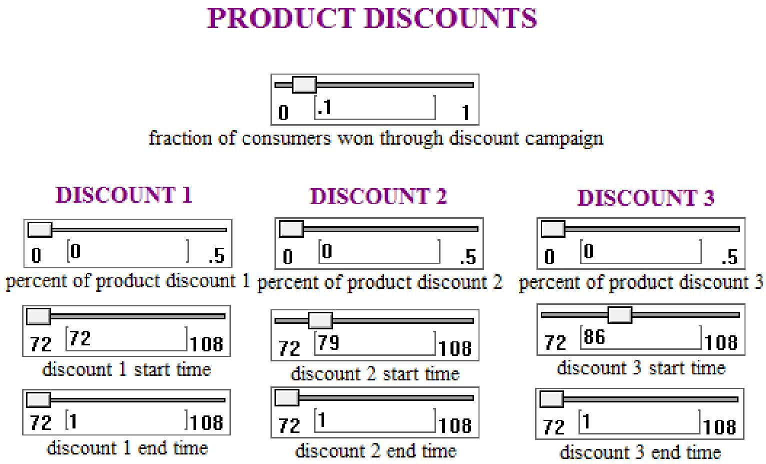


The appearance after clicking on Synthesym



3. The meaning of sliders

But let's first explain what each slider means. For better understanding, you can use the image of the whole model scheme (which was provided printed, or look at the scheme in S4.4).



When you make changes in product discount, this will affect how many products non-loyal and loyal consumers buy (you can look at the model scheme to see that; see variables in purple colour in the scheme). An assumption is that if there is a product discount, consumers will be able to buy more products with the same amount of money.

For each price discount, you can move sliders to change the values of the following parameters:

- "Percent of product discount" (from 0-0.5, with 0 meaning 0% price discount and 0.5 meaning 50% price discount)
- "Discount start time" (from 72-108, 72 being the beginning January 2019 and 108 being December 2021. This means that 73 is the beginning of February 2019, 74 is the beginning of March 2019, etc. Also, 72.25 would then be the beginning of the second quarter of January, or roughly, the second week of January).
- "Discount duration" (from 0 months - 36 months; you can also choose 0.25, which would roughly correspond to one week of a discount)

You can add 3 product discounts in one model test (discount 1, discount 2, and discount 3). Those three discounts can start and end at different times, and the percentage of each discount can be different.

Moreover, you can change the "fraction of consumer won through discount campaigns" (0-1, 0=0%, 1=100%). This will increase the winning rate of non-loyal consumers of the product.

4. Test 1a

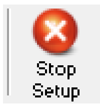
Let's do the first test now. Imagine you want to have a 20% discount in February 2019, and you want this discount to last for one month. This discount will affect non-loyal and loyal consumers to buy more products each month. Let's also assumes that because of this discount you will win 10% more Potential consumers, who will become Non-loyal consumers.

> Move the slider "percent of product discount 1" to the value 0.2.
> Look at the graphs and notice that a new line appeared, one blue and one red.
> Be careful, your base run will be in red colour now (not in blue anymore). Always read below the graph which line represents your base run, and which represents your current test.
> Move the slider "discount 1 start time" to 73.
> Move the slider "discount duration" to 1.
> Move the slider "fraction of consumers won through discount campaign" to 0.1

Now you see what would happen if you had a 20% discount for a month, compared to base run, when there is no such discount.

If you want to make the graphs bigger go to: View/Zoom/(choose 100% or 200% or custom)

To go back to the previous size: View/Zoom/Fit to screen

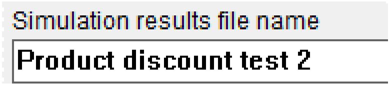
Once you are done, you can close this model run by clicking on 

.

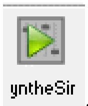
5. Test 1b

Imagine you want to permanently lower the price for 20% from February 2019. Let’s also assume that because of this discount you will win 10% more Potential consumers in that period.

1. Click in the field:



and give your run a name. For example “Product discount test 2”.

2. Now click on the button SyntheSym 

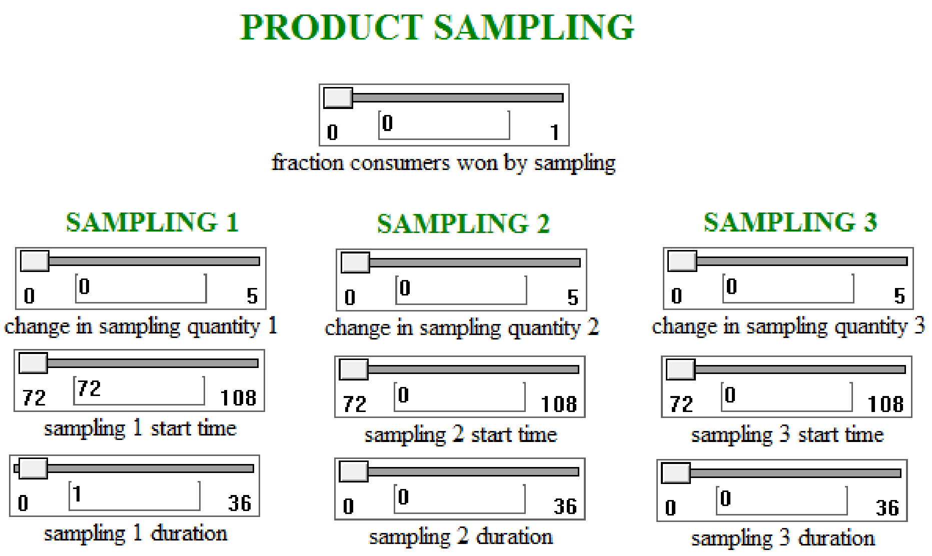
.

3. Move the slider “percent of product discount 1” to the value 0.2.
   Look at the graphs and notice that a new line appeared, one blue and one red.
   Once again, <u>be careful</u>, your base run will be in red colour now (not in blue anymore, the deficiency of the software). Always read below the graph which line represents your base run, and which represents your current test.
   Move the slider “discount 1 start time” to 73.
   Move the slider “discount duration” to 36.
   Move the slider “fraction of consumers won through discount campaign” to 0.1

4. Once you are done, click on 

.

Exercise 2: Product sampling



If you increase sampling, this will affect how many "new potential consumers" you get, but also how many current potential consumers you might win, who will become non-loyal consumers.

For each product sampling you can move sliders to change the values of the following parameters:

- "Change in sampling quantity" (from 0-5, with 0 meaning no sampling, 1 meaning double than currently, 2 meaning triple than currently etc.)
- "Sampling start time" (from 72-108, 72 being the beginning January 2019 and 108 being December 2021. This means that 73 is the beginning of February 2019, 74 is the beginning of March 2019 etc. Also, 72.25 would then be the beginning of the second quarter of January, or roughly, the second week of January).
- "Sampling duration" (from 0 months - 36 months; you can also choose for example, 0.25, which would roughly correspond to one week of sampling)

Moreover, you can change "fraction of consumers won by sampling" (0-1, 0=0%, 1=100%). This will increase the winning rate of non-loyal consumers of the product.

1. Test 2a

Imagine you want to double the sampling for one month, from January 2019. Also, this will allow you to win 5% more potential consumers

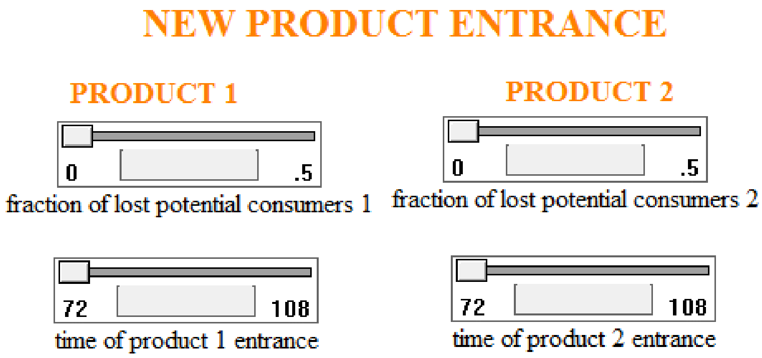
1. Give your run a name. For example “Product sampling test 2”.
2. Now click on the button SyntheSym
3. Move the slider “change in sampling quantity 1” to the value 1.
   Move the slider “sampling 1 start time” to 72.
   Move the slider “sampling 1 duration” to 1.
   Move the slider “fraction consumers won by sampling” to 0.05
4. Look at the graphs.
5. Once you are done, click on “Stop setup”.

2. Test 2b

Imagine you want to double the sampling for 3 years, from January 2019. Also, this will allow you to win 5% more potential consumers

6. Give your run a name. For example “Product sampling test 2”.
7. Now click on the button SyntheSym
8. Move the slider “change in sampling quantity 1” to the value 1.
   Move the slider “sampling 1 start time” to 72.
   Move the slider “sampling 1 duration” to 36.
   Move the slider “fraction consumers won by sampling” to 0.05
9. Look at the graphs.
10. Once you are done, click on “Stop setup”.

Exercise 3: Entrance of a new company product on the market



If you enter a market with a new product, which is similar to your product, this will affect how many current potential consumers you might win, who become non-loyal consumers (see orange variables in the model scheme in S4.4). In other words, if a new product enters the market, you will win less potential consumers, which means there will be less non-loyal consumers (and eventually less loyal consumers).

For each new product that enters the market you can move sliders to change the values of the following parameters:

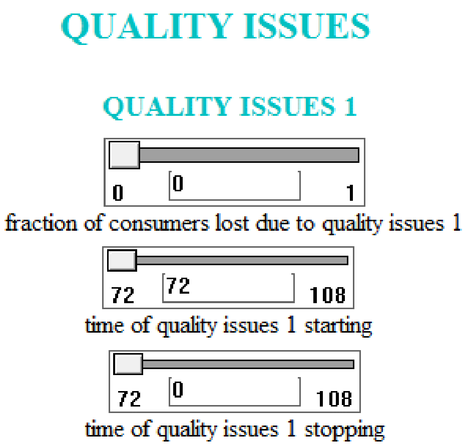
- “Fraction of lost potential consumers 1” (from 0-0.5; 0=0%, 0.5=50%)
- “Time of product 1 entrance” (from 72-108, 72 being the beginning January 2019 and 108 being December 2021. This means that 73 is the beginning of February 2019, 74 is the beginning of March 2019 etc. Also, 72.25 would then be the beginning of the second quarter of January, or roughly, the second week of January).

1. Test 3

Imagine you enter the market with a new product, from January 2019, which will make you win 2% less potential consumers.

2. Give your run a name. For example “New product test 1”.
3. Now click on the button SyntheSym
4. Move the slider “fraction of lost potential consumers 1” to the value 0.02.
   Move the slider “sampling 1 start time” to 72.
   Move the slider “sampling 1 duration” to 1.
5. Look at the graphs.
6. Once you are done, click on “Stop setup”.

Exercise 4: Quality issues



If you experience product quality issues, this will affect losing loyal consumers (see blue variables in the model scheme S4.4).

For each quality issue you can move sliders to change the values of the following parameters:

- “Fraction of consumers lost due to quality issues” (from 0-1; 0=0%, 01=100%)
- “Time of quality issues starting” (from 72-108, 72 being the beginning January 2019 and 108 being December 2021. This means that 73 is the beginning of February 2019, 74 is the beginning of March 2019 etc. Also, 72.25 would then be the beginning of the second quarter of January, or roughly, the second week of January).
- “Time of quality issues stopping” (from 72-108, 72 being the beginning January 2019 and 108 being December 2021. This means that 73 is the beginning of February 2019, 74 is the beginning of March 2019 etc. Also, 72.25 would then be the beginning of the second quarter of January, or roughly, the second week of January).

1. Test 4

Imagine you had quality issues with the product, from July 2019, for two weeks, which made you lose 1% more of loyal consumers.

1. Give your run a name. For example “Quality issues test 1”.
2. Now click on the button SyntheSym
3. Move the slider “fraction of consumers lost due to quality issues 1” to the value 0.01.
   Move the slider “time of quality issues starting” to 72.
   Move the slider “time of quality issues stopping” to 72.5.
4. Look at the graphs.
5. Once you are done, click on “Stop setup”.

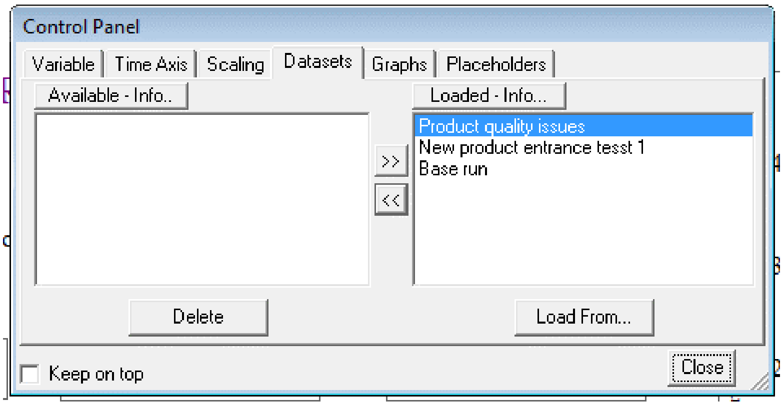
Practical issues

What to do when you have to many lines in graphs?

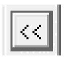
Click on 

and choose Datasets.

The window should look similar to this:

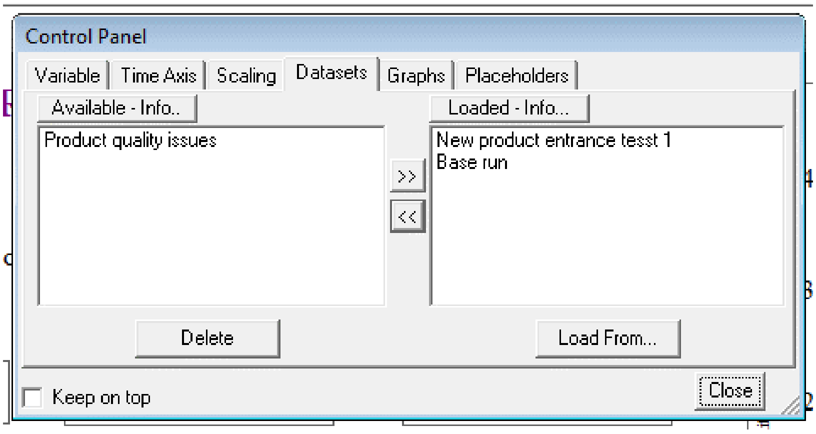


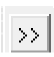
In the right box click on the test name you want to remove from the graph, for example "Product quality issues".

Then click on the sign 

.

The test will now appear in the left box and it will no longer be visible in graphs. To close to window click on **Close**.



If you want to make some of the tests you removed visible, click on the test name in the left box, and then click on the sign 

. To close to window click on **Close.**

8. Impact of the Vensim DELAY1 function on model behaviour*

Vensim's DELAY1(X, T) function represents a first order exponential delay of X for time T conserving X (Vensim, 2018). While this function can be useful to represent some model structures in a more condensed way, its use to delay stocks should be avoided. The impact of using DELAY1 function to delay the content of stocks will be explained in the following pages. All formulas are in Table S4.6.

An example model in Figure S4.5 contains DELAY1 function in the flow 2a. Figure S4.5. shows the impact of this function on behaviour of the Stock b1.

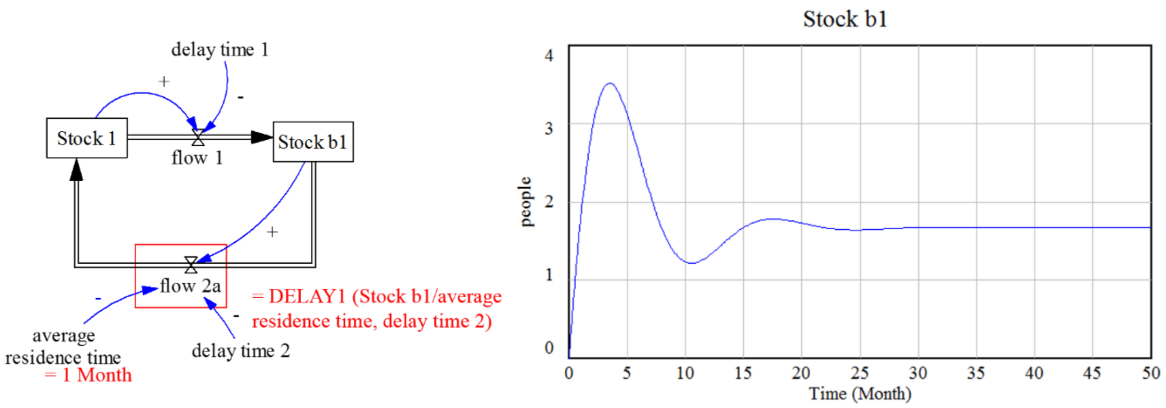


Figure S4.5. *Behaviour of a model structure when DELAY1 function in Vensim is used in a flow formulation.*

Normally, a first order delay could also be modelled more explicitly, which is illustrated in figure S4.6. In this case, the flow 2a in figure S4.5 is equal to the flow 2b in figure S4.6.

*We would like to acknowledge an anonymous opponent for their contribution to this section by explaining consequences of the use of DELAY1 function in Vensim.

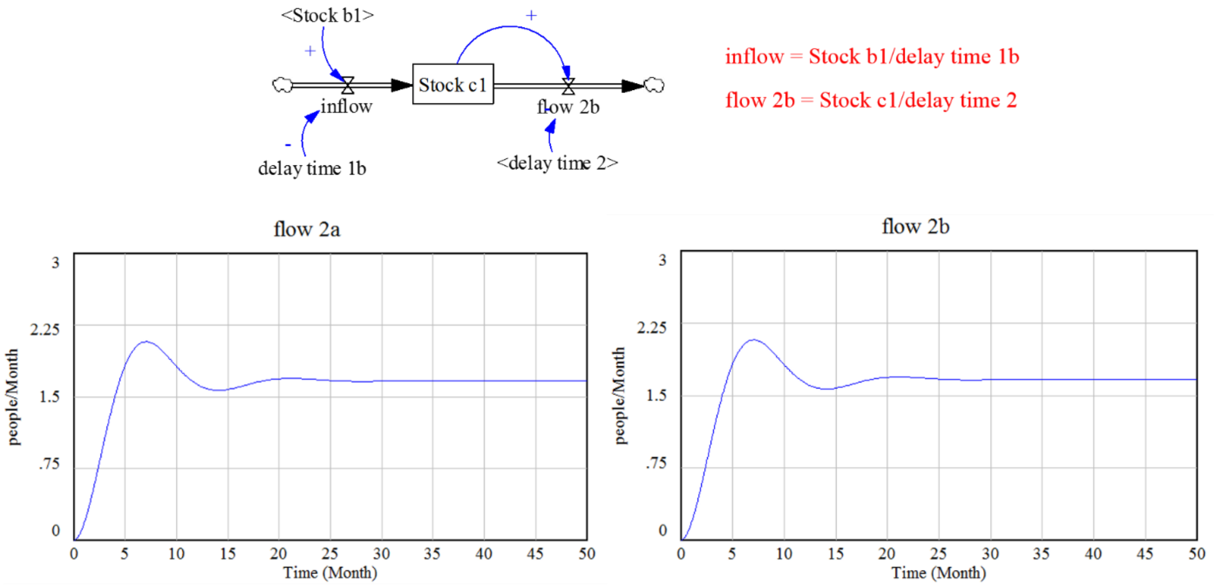


Figure S4.6. *An explicit structure of DELAY1 function.*

If we add an explicit structure of the first order delay to the model structure in figure S4.5, we obtain a model structure and behaviour represented in figure S4.7. In that case, the model behaves differently, which can be seen by comparing behaviours of the Stock b2 in figure S4.7 and the Stock b1 in figure S4.5.

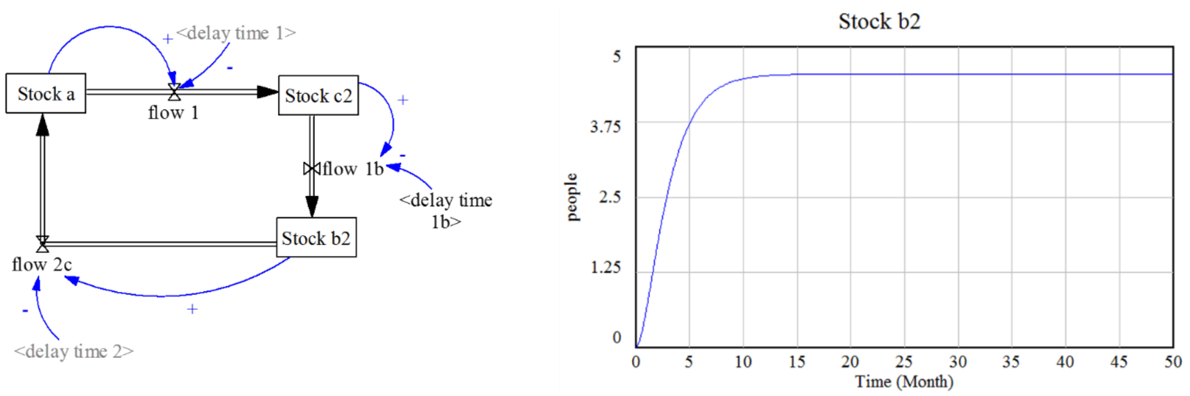


Figure S4.7. *Model structure and behaviour when an explicit structure of DELAY1 function is added to the model in figure S4.5.*

To obtain the same model behaviour as presented in figure S4.5, the structure needs to look as shown in figure S4.8. The flow 1c is not only based on the Stock c3 but also on the Stock b3. A positive feedback loop is added to the balancing system. Now, behaviour of the Stock b1 in figure S4.5. is equal to the behaviour of the variable “sum of stocks” in Figure S4.8.

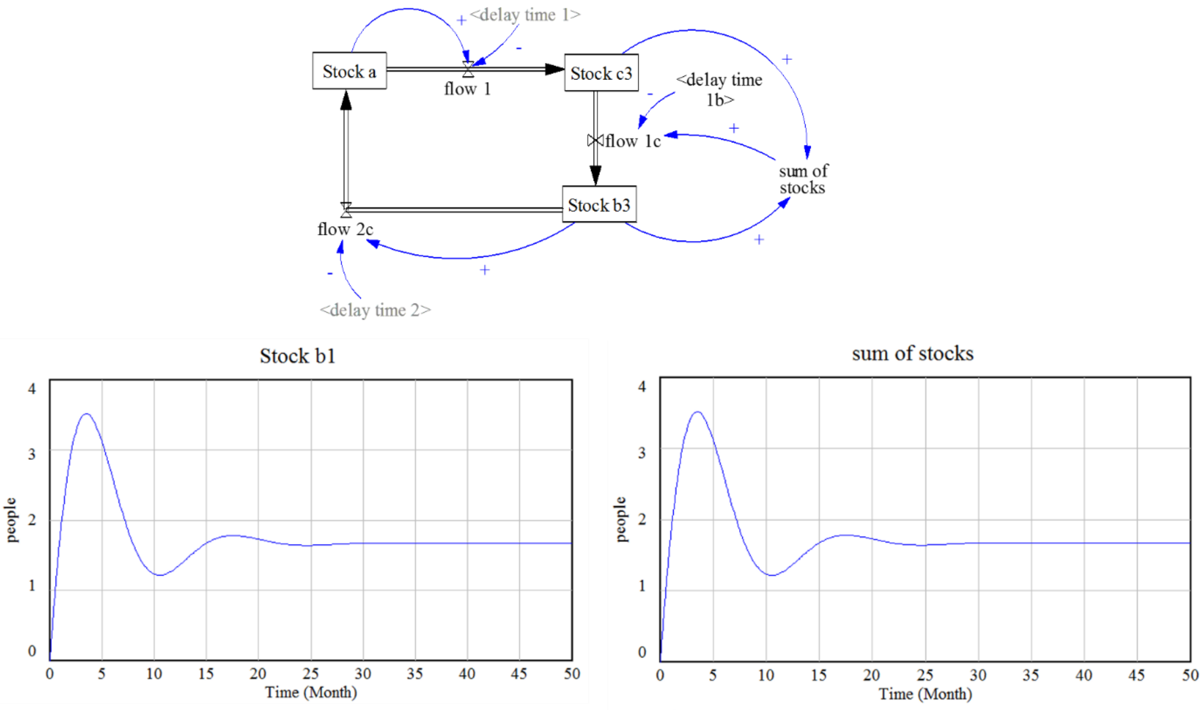


Figure S4.8. *Comparison of the behaviour of the Stock b1 and the “sum of stock” variable.*

Figure S4.9 shows that in the case of the model structure in figure S4.8, the Stock c3 becomes negative, which does not properly represent reality, especially in a situation when stocks contain people. This happens because the outflow of the Stock c3 is based on the “sum of stocks” variable and can be larger than the value of Stock c3.

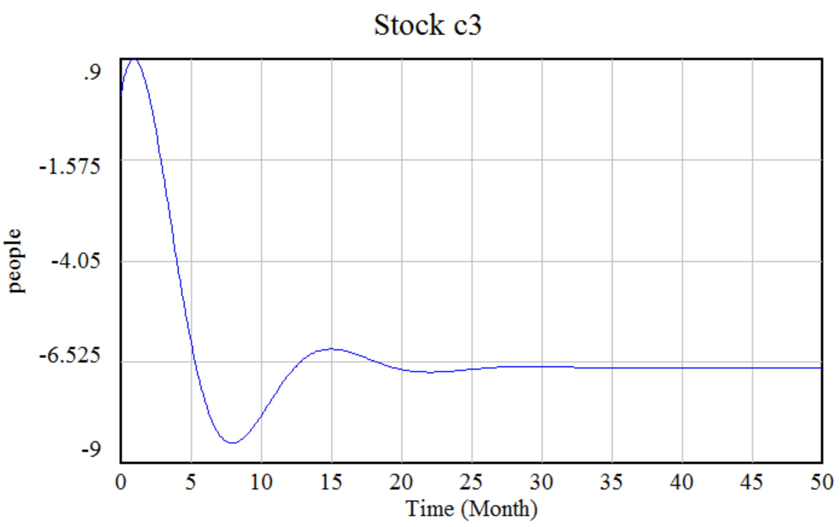


Figure S4.9. *Behaviour of the Stock c3 from the figure S4.8.*

Table S4.6. *Formulations of the variables of the Vensim models* from figures S4.5 to S4.8.*

Variable name	Unit	Formulation
Figure S4.5		
Stock 1	people	= ∫ flow 2a – flow 1 dt + [10]
Stock b1	people	= ∫ flow 1 – flow 2a dt + [0]
flow 1	people/Month	= Stock 1/delay time 1
flow 2a	people/Month	= DELAY1(Stock b1, delay time 2)
delay time 1	Month	= 5
delay time 2	Month	= 5
average residence time	Month	= 1
Figure S4.6		
Stock c1	people	= ∫ inflow – flow 2b dt + [0]
inflow	people/Month	= Stock b1/delay time 1b
flow 2b	people/Month	= Stock c1/delay time 2
delay time 1b	Month	= 1
Figure S4.7		
Stock a	people	= ∫ flow 2c – flow 1 dt + [10]
Stock c2	people	= ∫ flow 1 – flow 1b dt + [0]
Stock b2	people	= ∫ flow 1b – flow 2c dt + [0]
flow 1	people/Month	= Stock a/delay time 1
flow 1b	people/Month	= Stock c2/delay time 1b
flow 2c	people/Month	= Stock b2/delay time 2
Figure S4.8		
Stock c3	people	= ∫ flow 1 – flow 1c dt + [0]
Stock b3	people	= ∫ flow 1c – flow 2c dt + [0]
flow 1c	people/Month	= sum of stocks/delay time 1b
sum of stocks	people	= Stock c3 + Stock b3

*time step: 0.125, integration: RK4 Auto, initial time: 0, final time: 50, units for time: Month

Reference:

1. Vensim DSS. (2018). Harvard: Ventana Systems, Inc.

Summary

The development of new food products has been a major driver of growth for food industry. However, it has been challenging for food companies to develop new products that would become successful among consumers on the market. Some of the challenges result from numerous actors participating in decision-making who need to establish a multitude of product characteristics. Moreover, consumers' needs change over time, which makes it even more difficult to identify if a product will be successful. Since the factors that contribute to product performance on the market are interconnected, this complicates understanding of their impact on product success over time. Therefore, an approach that can capture the dynamic and complex nature of food product success is needed to facilitate decision-making and to increase product success chances. In this thesis, systems thinking and system dynamics approaches were employed to identify mechanisms relevant to understand complex dynamic aspects of food product performance. Systems thinking and system dynamics are approaches that allow identification of feedback processes relevant to understand dynamic aspects of food product success, while taking into account perspectives of multiple actors, i.e., technology, marketing, and consumer research. Therefore, the aim of the thesis was to developing qualitative and quantitative systems thinking and system dynamics models, which could provide insight into dynamic feedback processes relevant for understanding food product performance, from the perspective of different functions participating in new product development (NPD) and the product life cycle PLC.

In Chapter 1, the problem of high failure of new food products is discussed. Various aspects contributing to the complexity of new food product performance and to high failure of new products are described. Moreover, the need for an approach that would capture dynamic complexity of food product performance is justified and systems thinking and system dynamics approaches to study dynamic feedback processes affecting product success are suggested. Lastly, the objective and outline of the thesis are described.

Chapter 2 represents a study on the extent to which European food companies use three types of consumer data, i.e., consumer involvement, food trends, and environment factors data in

different NPD and PLC phases, and what data collection methods they employ. The three data types are differentiated based on time frame, which represents the relative length of the period in which consumer data are obtained, and specificity, as relating to a particular product. The results showed that all three data types are used to a similar extent within different phases of NPD and the PLC, with the exception of product testing phase of NPD. In this phase, the respondents use much more frequently consumer involvement data. However, all three data types are significantly less used in the PLC than in NPD, which could indicate that the respondents assess the degree of fit between a product and consumers' needs to a lesser extent in that phase. Moreover, respondents often use formal methods to collect consumer involvement data, but not to collect food trends and environmental factors data. Lastly, respondents rarely employ simulation-modelling methods, such as system dynamics, which could indicate a lower consideration and understanding of dynamic feedback mechanisms that influence product success.

In Chapter 3, the objective was to increase understanding of the feedback processes that are important to dynamically assess performance of a new food product, i.e., to anticipate how product performance might change over time. A literature review was performed to understand what factors, from the perspective of three functions: marketing, technology, and consumer research, are crucial in understanding food product performance. The findings of the structured literature review were presented in the form of causal maps with feedback loops, i.e., means-criteria diagrams, which were then synthesized in an integrated framework for dynamic assessment of performance of a new food product. This process revealed 46 variables, four balancing and seven reinforcing feedback loops, that are relevant for dynamic assessment of food product performance. The integrated framework captured the dynamic nature of the new food product performance in a single image. Moreover, it showed the cause-effect relationships between the actions of one function in a food firm and consequences of these actions for the overall product performance.

Although feedback loops give an indication of a possible evolvement of product performance over time, the exact dynamic behaviour can only be uncovered if a system dynamic simulation model of a specific product, or product category, is developed. Therefore, in Chapter 4, the development of a system dynamics model is demonstrated for a case of insect-based food adoption in the Netherlands. The model was developed based on a structured review of literature on edible insects and on the innovation of diffusion paradigm, which were used to extend the existing Bass diffusion system dynamics model on adoption of consumer durables.

Once developed, the model was used to discuss the potential of system dynamics modelling and simulation in understanding the adoption of radical new food. Model simulations revealed that the diffusion of an insect-based food, such as an insect-based burger, will be a long process, under the currently reported practices in the Netherlands. The main mechanism that can strongly affect diffusion of such food is word-of-mouth, occurring after a positive tasting experience. The research presented in Chapter 4 was also beneficial in uncovering knowledge gaps that need to be addressed to increase understanding of the problem of radical food product success.

Chapter 5 describes the development of a system dynamics model with a group of stakeholders from a food company, by employing a group model building approach. Group model building involves developing a system dynamics model, which was in this case used to understand a complex dynamic problem of stagnating sales of a healthy snack. A system dynamics model was built together with the people from different company functions (i.e., marketing, sales, production, and quality). The approach was useful in explaining that product sales are oscillating and have multiple consecutive cycles of increasing and decreasing sales. This is because a company attracts many non-loyal and loyal consumers through marketing campaigns, which causes an increase in product sales. However, there are also feedback loops causing the loss of one part of those consumers, which leads to a delayed effect in sales decrease. Group model building was successful in increasing participants' insight into the causes of the sales problem, in improving communication, and in creating shared vision about the problem, which can all have a positive impact on developing successful strategies to improve performance of their product.

In Chapter 6, general discussion of the findings of the thesis is presented. It starts with a description of the main findings, followed by theoretical contribution, methodological considerations, and implications for future research. Finally, recommendations for practitioners and main conclusions are described.

Acknowledgments

"Ow! My brains!"
Douglas Adams, The Hitchhiker's Guide to the Galaxy

Doing a PhD is a perfect way to meet, work, and not work with many people. It is great that I get to use the final pages of this thesis to acknowledge them for their work and non-work contributions. Since everyone knows that work comes first, and then play, let us first give credit to many smart people I worked with on this thesis.

Pieternel is a master of planning every second of her day. I was very lucky to be able to get into her busy schedule, starting with the first Skype interview more than 5 years ago. I am grateful that I got a chance to learn how to be a scientist from a person who so passionately shares her vast knowledge with her students. Thank you for always believing in my research!

Vincenzo is a master of working at any time and place humanly possible. I think I will never forget an e-mail at 1 am on Thursday with which you informed me that I was selected for this PhD position. Of course, I woke up half of the house! Your skill to motivate people amazes me and I hope that one day I will understand how you can do it so effortlessly.

Thank you both Pieternel and Vincenzo for giving me endless amounts of freedom in performing the research presented in this thesis.

Behzad, thank you for jumping in in the middle of this (sometimes) vague project. My third chapter would not be possible without you introducing me to the world of policy analysis, which I find very interesting.

Giulia, you started as my master student, continued as my trusted research assistant, and ended up becoming my PhD colleague (although in a different department). I enjoyed working with you and you are very fun to be around. I wish you never have to walk around Anuga asking people to fill out a survey again.

David, thank you for being on a mission of spreading system dynamics knowledge. I was lucky enough to get to know you through our peer-mentoring meetings. My fifth chapter would never be so successful without your input. It is impressive how easily you are able to turn scientific papers into captivating stories.

Henry, we started as colleagues at Radboud University. I enjoyed working with you on the project described in the fifth chapter and I am thankful that you gave me an opportunity to practice my group model building facilitating skills through DynaMundo.

Kimberley, Corine (and Lysanne), nothing in FQD would be possible without you. I hope you will always stay as funny, nice and professional as you are!

There are some people who did not work with me on the thesis, but who contributed to making me distracted from the research I was supposed to be doing, for which I am grateful!

My (ex)colleagues with whom I organized a PhD trip to Italy in 2016 (Ana, Ayusta, Isabelle, Jonna, Valentina). If we forget the initial frustration related to funding, I think the organization went smoothly and I am very proud of us for that. Valentina and Isabelle, I hope you also think of me when you hear the song This Girl from Kungs vs Cookin' on 3 Burners. Thank you for all the fun moments!

My current and ex peers from the Product and innovation management peer-mentoring group (Emiliya, Felix, Lan Anh, and our system dynamics expert member David Andersen). It is amazing that we have managed to keep these meetings going in between many continents (Australia, Europe, North America, and shortly even Asia) for three years (and counting)! Thank you for keeping me motivated to do system dynamics!

All the past and present colleagues from the Student Chapter of the System Dynamics Society and beyond. We have done some great voluntary work for system dynamics students all over the world. Emiliya and Max, you have been my party animals ever since the first System Dynamics Conference in 2016 in Delft, which continued in Cambridge, USA in 2017, and in Reykjavik in 2018. I was happy to also have you as travel companions in Iceland. Thank you, Emiliya, for providing caffeine pills to keep me awake during the conference!

What would a PhD be without many colleagues who are there just to lighten up your day by discussing the most random things. Thanks for sharing your wise (and, luckily, not always wise) thoughts during lunch: Femke, Pieter, Arianne, Ayusta, Lucia, Evita, Jonna, Julie, Sara, Fabiola, Ana, Mostafa, Sine, Dario, Burce, Etske, Mike, Erik, Kimberley, Edoardo, Ornella, Teresa, Ita. Honourable mention goes to Domenico who left FQD as an unproclaimed master of random lunch topics (but now I wrote it down so your title is official, come to pick it up at my defence party). Finally, Annelies, thank you for your Dutch translations and a/the corrections.

Hannah does not normally eat (much) but deserves to be thanked for initiating numerous Friday beers (this paragraph goes with the soundtrack of Rebecca Black's Friday) and karaoke evenings, which I (fortunately or unfortunately??) always had to attend since I have the karaoke machine. Jonna was our party room provider. One dear friend of mine once called me a music snob (glazbeni snob), which has been one of my favourite insults ever since (although I see it as a compliment). Well, let us just say that these karaoke evenings made me a bit less of that!

I was among the first to become a victim of flex desk in FQD. Over the past years, I got to sit with many colleagues who made the flex desk experience less annoying. Daphne and Sydney, one of the early flex desk victims, I always enjoyed our chats. Sara, Mohammad, Hao, Yajing, Zhijun, since we lost our ground floor office, we need to start working on which office to conquer next.

Many more contributed to making this PhD in FQD (and outside) an enjoyable experience: Chunyue, Faith, Renske, Elsa, Daylan, Ruben, Jing, Naomi, Alim, Lijiao, James, Mary Luz, Ruth, Juliette, Bernard, Shingai, Onu, Moheb, Michele, Ling, Li, Jilu, Anita, Matthijs, Jenneke, Klementina, Eline, Edurne, Grace, Geraldine, Sara, Marine, Charlotte, Frans, Marielle, Kasper, Hein, Bea, Nicoletta, Yingxue, Fahui, Elsbeth, Catriona, Hilde, Antonija, Ante, Barry, Aditya, Yao, Tiny, Ruud (our story starts after my PhD - thank you for all the nice chats and business travels). Please forgive if I forgot to mention you, I would be glad to hear your complaint to get a chance to chat with you.

I am very grateful to my paranymphs Jonna and Valentina. You are almost there as well! I wish you a lot of success. Valentina, thank you for introducing me to the Look What the Cat Dragged In. What would life be without seeing their performances? Jonna, the mother of chickens, thank you for having amazing organizational skills, which made organizing the PhD trip seem very simple.

Surprisingly, there is life outside of the office walls! Sara and Sven (Lotte & Berry), thanks for having me at your party house and for a lot of good food and tasty cocktails. Steve, thanks for your good music taste and for showing me Grizzly Bear. Your house is the place with the best music in Wageningen. Mali and Leo, it is always nice to complain to someone about the life in Wageningen over drinks. Aleg, Marit, Max, thank you for the Russian adventure.

There are also some nice people I left behind when I left Croatia. Thanks Ivana and Tea for putting up with me since we were seven, we should celebrate our silver anniversary (srebrni pir) this year. Ivana, thank you for being a consistent provider of partying experiences in Koprivnica and Zagreb for more than a decade. Tanja, you are my diary. Ever since I left Croatia, I have problems with recalling the past. Dario, you are such a good person, it is wonderful to have an anchor in Koprivnica. Ema, your motivation to always work extra hard is impressive. I hope that one day you will impress me with your cooking skills as well. Ivan, thank you for providing studying resources so that I could get higher grades, you are part of the reason I am here. I am glad we stayed friends even after our master’s. Marko, you came into my life unexpectedly and in a very strange phase. I am very happy that you stayed. I want only the very best for you, especially in terms of shirts from exotic countries with even more exotic patterns.

People who have had to put up with me the longest – my family. To my brothers Andrej and Marin, I have to thank you especially from a logistics perspective. Who could count the times you had to drive me to Zagreb and back, to the train station and back, to the airport and back. Having two older brothers taught me to be relentless in fighting for what I want. I wish you to do things in life that will make you fully happy. Đurđica, thank you for surprise birthday parties, repeated birthday parties and postcards. Thanks to you, I keep being on family photos! Hello to my nephews Petar and Matej and to my niece Sara. It is time to start learning English to read this!

I would like to thank my mum for accepting that I will usually do whatever I think is best for me, even though she sometimes does not agree with everything. While I have never liked to study (in the classic sense of memorizing things), I often used studying as an excuse not to do many things that I hated even more than studying. She would always tolerate my excuses. I guess that paid off in the end. This thesis is for you! Finally, thank you for passing on to me your baking skills. I am sure my colleagues are also grateful for that!
Htjela bih se zahvaliti mami na tome što se pomirila s time da ja ću ja obično napraviti ono što mislim da je najbolje za mene, iako se ponekad ne slaže sa svime. Iako nisam voljela učiti (pamtiti informacije napamet), često sam učenje koristila kao izgovor kako ne bih morala raditi druge stvari koje nisam voljela više od učenja. Ona bi uvijek tolerirala moje izgovore. Pretpostavljam da se to na kraju isplatilo. Mama, ovaj doktorat je za tebe! Osim toga, hvala ti što si na mene prenijela umijeće pečenja kolača. Sigurna sam da su i moji kolege zahvalni!

Thank you, lucky Rui! You have been the most eager promoter of my research, by telling everyone that I build models of other people's opinions (which is not even completely incorrect). You are a constant provider of information that I normally do not think I need and of jokes I do not want to hear. Usually, I forget everything people say, while you repeat everything a hundred times. That way I can memorize things and use it as conversation topics later on. Without you my life would be with too much organization, too little Friday nights out, and just not enough fun.

Lastly, if someone has not had enough of science or blabber by now, I highly recommend the paper by Goldschmidt (2016). It will serve as a refreshing breeze at the Rhine surrounded by cows, an icy gin tonic, or a big piece of my cake – whatever is your preferred relaxation starter.

Reference

1. Goldschmidt, T. (2016). A Demonstration of the Causal Power of Absences. Dialectica, 70(1), 85.

Overview of completed training activities

Course/activity name*	Organizer and location*	Year
Discipline specific courses and activities		
Courses and trainings		
Connect4Action final academic training: Improving communication between food technologists and consumer scientists during the food innovation process	Connect4Action, Brussels, Belgium	2014
AnyLogic software training	The AnyLogic Company, Paris, France	2014
Measuring and modelling dynamics in innovation systems	Utrecht University, Utrecht, The Netherlands	2015
Continuous systems modelling	TU Delft, Delft, The Netherlands	2015
Sensory perception and food preference	VLAG, The Netherlands	2016
3rd system dynamics summer school (intermediate level)	TU Delft, Delft, The Netherlands	2016
4th system dynamics summer school (advanced level)	MIT, Cambridge, USA	2017
Conferences		
Joint final conference of RECAPT and Connect4Action on collaborative innovation in the food sector	RECAPT & Connect4Action, Brussels, Belgium	2014
2nd Wageningen PhD symposium	WPC, Wageningen, The Netherlands	2015
34th international conference of the System Dynamics Society *(poster presentation)*	System Dynamics Society, Delft, The Netherlands	2016
35th international conference of the System Dynamics Society *(two poster presentations)*	System Dynamics Society, Cambridge, USA	2017
31st EFFoST international conference *(oral presentation)*	EFFoST, Sitges, Spain	2017
12th international European forum on system dynamics and innovation in food networks *(oral presentation)*	Universität Bonn, Igls, Austria	2018
36th international conference of the System Dynamics Society *(poster presentation – Poster of Excellence Award)*	System Dynamics Society, Reykjavik, Iceland	2018
Benelux Chapter system dynamics conference *(oral presentation)*	Benelux Chapter of the System Dynamics Society, The Hague, The Netherlands	2018

General courses and activities		
VLAG PhD week	VLAG, Wageningen, The Netherlands	2015
Systematic approaches to reviewing literature	WASS, Wageningen, The Netherlands	2015
Information literacy including EndNote introduction	WGS, Wageningen, The Netherlands	2015
Applied statistics	VLAG, Wageningen, The Netherlands	2016
Scientific writing	WGS, Wageningen, The Netherlands	2016
Career perspectives	WGS, Wageningen, The Netherlands	2018
Optional courses and activities		
Preparation of the PhD research proposal	FQD, Wageningen, The Netherlands	2014-2015
FQD colloquia	FQD, Wageningen, The Netherlands	2014-2018
Organizing the PhD study trip to Italy	FQD, Wageningen, The Netherlands	2015-2016
Group model building 1	Radboud University, Nijmegen, The Netherlands	2015
Group model building 2	Radboud University, Nijmegen, The Netherlands	2015-2016
PhD study trip to Italy	FQD, Italy	2016
Socio-technical systems discussion group	FQD, Wageningen, The Netherlands	2016
System dynamics peer-mentoring online meetings	Student Chapter of the System Dynamics Society, online	2016-2018

*Abbreviations:

WPC - Wageningen PhD Council

VLAG – The Graduate School VLAG

MIT - Massachusetts Institute of Technology

WASS – Wageningen School of Social Sciences

WGS – Wageningen Graduate Schools

FQD – Food Quality and Design Group

About the author

Andrijana Horvat was born on the 20th of October 1987 in Koprivnica, Croatia, where she finished her primary and secondary education. In 2006, she started her bachelor studies in Food Technology at the University of Zagreb, Faculty of Food Technology and Biotechnology. She completed her bachelor's degree with the highest average grade among her Food Technology colleagues, and she wrote a thesis entitled High-intensity ultrasound aided apple drying. She was awarded a scholarship of the Biotechnical Foundation of the Faculty of Food Technology and Biotechnology for her bachelor thesis work. In 2009, she started master study Food Engineering at the same faculty. In 2010, she was awarded a mobility scholarship CEEPUS (Central European Exchange Program for University Studies) to study at the University of Natural Resources and Life Sciences (BOKU) in Vienna, Austria, where she was following courses from the Safety in the Food Chain master study. She finalized her master's degree in 2012 at the University of Zagreb with the thesis entitled Influence of composition on sensory and textural properties of chewing gum. After her studies, she started her industry career at Carlsberg Croatia, where she worked as an SAP operator for logistics and finance departments, and later on at Podravka, where she worked as a product developer of Dolcela powdered desserts for home baking. In 2014, she decided to return to academia and she started a PhD program at the Food Quality and Design Group (FQD) of Wageningen University and Research, The Netherlands. The results of her PhD research are presented in this thesis. During her PhD study, she had an opportunity to work as a system dynamics consultant with DynaMundo on industry and academic projects. She was also active in the System Dynamics Society, first as secretary and then as president of the Student Chapter of the System Dynamics Society. Currently, Andrijana is working as a postdoctoral researcher at FQD on ProOrg EU project related to developing a Code of Practice for organic food processing.

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