Improving neighborhood-specific overweight policy in the Netherlands using a system dynamics approach

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Executive summary

More and more people are experiencing an unhealthy, excessive weight status. It is expected that the proportion of overweight people will only continue to increase in the coming years. So far, interventions to prevent and reduce overweight were primarily developed to approach the problem from an individual perspective. Evidence exists that not only individual factors but interactions between a variety of biological, social, economic and environmental factors is attributed as causes of gaining weight. An integrated approach involving cooperation between various disciplines therefore seems to offer the possibility of tackling the problem effectively. Partly for this reason, the Dutch national government decentralized the approach for tackling overweight in 2018 to municipalities, which are now responsible for it.

The problem is that it remains difficult for local policymakers to select an appropriate set of policies for a given neighborhood. Each neighborhood has characteristic features affecting the increasing number of overweight people. Although many different policy interventions are described and suggested, a measure that works in one neighborhood is not necessarily effective in another one. A way to explore the effectiveness of possible policy interventions ex ante their introduction is not available to date and therefore desirable. The research question central to this study concerns:

What combination of local policy interventions can be deployed to reduce overweight at the neighborhood level?

To address this research question, the System Dynamics modeling method was applied. The objective of the research is in line with the objectives sought to be achieved by an SD model. First of all, it allows one to study the problem from a high aggregation level and thus to investigate different determinants and relationships of the complex problem. In addition, this continuous simulation method provides for modeling the structure of systems in which feedback structures occur, as with the current topic where the weight affects the level of activity and that in turn affects the weight. The steps described for conducting an SD study were followed and involve: problem identification, model conceptualization, model formalization (quantification), model testing and model use.

The Dutch organization for applied sciences (TNO) together with Partnerschap Overgewicht Nederland (PON) viewed the problem from various perspectives in order to establish an Individual Overweight model, revealing a variety of factors that lead to overweight and their interrelationships. The Individual Overweight model has played an important role in providing insight into various domains that contribute to becoming overweight, such as mental, social, economic and environmental influences. These insights have been used in the conceptualization phase to identify the domains that influence the growth of the overweight population at neighborhood level.

During the conceptualization phase in which a causal loop diagram and a stock and flow diagram were combined to give an overview of the structure of the system, it was found that three sub-models could be arranged to meet the objective of the model. The first and second submodels concern energy expenditure and energy intake, respectively. The energy expenditure submodel includes the three mechanism responsible for expenditure: resting metabolism, activity thermogenesis and food-induced thermogenesis. Here, activity thermogenesis is again influenced by aspects such as exercise, walking and cycling. For energy intake, a distinction was made between intake from food and non-alcoholic beverages, alcohol consumption and as a result of the food environment. Choice of classification into these three aspects came from differences in determinants, such as ethnicity and socioeconomic status, of these aspects. All these elements of intake and expenditure together determine energy imbalance, which is included in the third model. The third submodel focuses on the degree of overweight among the population. During the conceptualization phase, three feedback loops, mechanisms that have a self-reinforcing or balancing effect, were identified. The first of these affects the level of activity, the other two impact metabolism. This first feedback loop runs from average weight to degree of physical activity and back again to average weight, a reinforcing effect. The second feedback loop involves the effect weight gain has on metabolism during activity and the impact of this metabolism on weight. And the third feedback loop relates to influence of weight on resting metabolism, which in turn affects weight, again a balancing effect.

The Schildersbuurt in The Hague was chosen as a sample neighborhood for data implementation because there is a high prevalence of overweight in this neighborhood, making policy recommendations on overweight measures here useful, and because there is a relatively large amount of data available on this neighborhood. The base case simulation shows that in a situation where no policy measures are introduced, the rate of overweight among the Schildersbuurt population increases from 58% to about 60% between 2015 and 2026. The slight increase in the number of overweight people is explained by a positive energy imbalance, meaning that the average food intake of people in the population is greater than their average kcal expenditure. Verification and validation tests such as an extreme values test, sensitivity analysis, and historical data validation were conducted to test the model’s performance in reproducing real world behavior. It was concluded that the model is compatible for modeling overweight in the Schildersbuurt given the results of these tests. For instance, the behavior of the model was explanatory for small changes in the value of certain parameters. Furthermore, the historical validation test showed that the model's behavior is in line with historical values, however, the model's values did not exactly match the historical data. However, the model is suitable for finding possible local policy interventions and for evaluating the extent to which these measures are effective in reducing overweight on a neighborhood level.

Five different interventions were tested in the model:

- *Lifestyle as medicine*: an intervention in which people are encouraged to walk more as well as being educated about healthy food, increasing their knowledge about this topic.
- *Revised environmental law*: a change in legislation allowing municipalities to prohibit the establishment of unhealthy food suppliers in specific areas.
- *Improving bicycle network*: improving the bicycle infrastructure in the neighborhood which invites people to cycle more.
- *Eurofit in the neighborhood*: An integrated lifestyle intervention that targets the food intake of people with low socioeconomic status (SES) and also stimulates the daily activity of people in the neighborhood.
- *Building an outdoor gym*: facilitating public fitness equipment with the aim of increasing people's sports activity.

The model is subject to uncertainties because the exact value of parameters in the model is not known, such as, for example, the average walking time of people in the neighborhood. The uncertainty analysis revealed that the uncertain parameters, the ones with uncertain values, which have the most influence on the model behavior involve physical exertion during daily activities and physical exertion during sports activities. The effectiveness of the five interventions has therefore been tested under a broad set of configurations, defined by the uncertainties of these two parameters.

The policies *Lifestyle as medicine* and *Eurofit in the neighborhood* showed the best results in the experiments in the model, taking into consideration the uncertainties in the model. The measures have the potential to cause a significant decrease in energy intake and increase in energy expenditure, therefore achieving a substantial change in the value of the energy imbalance over time. This change can be partly explained by the fact that these measures target a determining factor of energy intake from food and non-alcoholic drinks, namely the nutritional knowledge of people in the neighborhood. The other tested measures also affected the energy balance negatively, but their effect was too weak to outweigh the impact of increasing energy intake. This was either because the parameters addressed by these measures have little effect on overall model behavior or because the change in value for the related parameter of this measure is to weak to generate a change. As a result, the energy imbalance remained positive leading to an increase in the overweight population over time. The advice for local policymakers in the Schildersbuurt is therefore to explore the options for implementing the *Lifestyle as medicine* and *Eurofit in the neighborhood* measures. Combined lifestyle interventions such as these appear to be an effective means of reducing overweight among the population in a neighborhood such as the Schildersbuurt.

The model has proven capable of providing policy advice for policymakers the Schildersbuurt. Moreover, this advice is consistent with previous recommendations for an integrated approach across disciplines. One of the limitations of the study includes the lack of data available for quantifying model parameters which required many assumptions for the input of parameters of the model to be made. The model also has limitations in terms of its scope, e.g., age groups are not included even though they could affect the metabolism and therefore energy expenditure.

Previous studies on the subject of overweight on neighborhood level have focused on a quantitative approach to the problem of populations in other countries (of which the results are not representative for Dutch neighborhoods) or on a qualitative approach to the Dutch population. A simulation model to provide specific policy advice for the Netherlands was still lacking. The study thus filled a gap in the literature and its scientific relevance lies in the integration of information from the literature into a model in which ex ante effects of policy interventions in the Schildersbuurt can be examined. This thesis bridges theoretical knowledge and specific local policy recommendations regarding the increasing level of overweight. The social relevance of this study envisages supporting local policy makers in making an informed choice about which policies to introduce. In addition, the study provides insight into the variety and impact of factors that play a role in the problem, thereby increasing support for the usefulness of an integrated approach.

For future research, it is recommended to collect more data of the precise effects of factors at the neighborhood level. Also, the scope of the research could be expanded by adding age subgroups in order to improve the model's behavior. Another recommendation is to test the usability of the model for other neighborhoods and use these insights to improve the model's behavior, so that the model can serve as a general tool for advising Dutch neighborhoods on policy interventions regarding tackling overweight.

Reflection on the method revealed that SD was appropriate for the high level of aggregation of the study, namely the neighborhood level. However, there are also elements in the system that act on an individual level, such as energy imbalance. Therefore, it is recommended that this study is combined with an Agent-based modeling (ABM) method, because Agent-based models are suitable for modeling individual agents with which behaviors at a lower level of aggregation can be examined.

Preface

In recent years, I have become more interested in adopting a healthy lifestyle (including exercising, doing yoga and healthy eating) because of its positive impact on the overall state of being. A year ago when I was thinking about a possible topic for my thesis the idea popped up of addressing a health problem in combination with a modeling technique and preferably the system dynamics method because I felt most familiar with it. By the end of 2019, I came across an assignment on addressing overweight at the neighborhood level in collaboration with TNO that immediately caught my attention. This assignment matched my interests and skills. After a few consultations it was settled, this was going to be my graduation project.

There are a number of people who made important contributions to the gathering of knowledge for this thesis. I would like to thank T. van de Broek for doing data analyses, W. van Bijsterveld, who helped me get the right data for the model and Prof. J. Seidell, with all his knowledge he helped me significantly with the scope and structure of my model.

Although in the beginning I was apprehensive about writing my thesis, due to stories I had heard about it, I have enjoyed working on it these past months. It was nice to work on my own project and to learn more and more about the determinants that play a role in becoming overweight. I was always told beforehand that a pleasant collaboration with your supervisors is one of the most important ingredients for an enjoyable graduation time, and I can only agree. My supervisors at TNO, Teun and Heleen, have a lot of knowledge on the subject of overweight and during weekly meetings they helped me to become familiar with the subject and supported me in making important choices (e.g. concerning the scope of the research). Their enthusiasm about the subject was contagious. Els, my first supervisor, was always available for questions regarding my model or if there were other issues I wanted to discuss. Whereas by nature I can be quite stressed at times, Els' guidance was ideal, in addition to substantive knowledge she also reassured me, something I am very grateful for. The second supervisor from the university, Jan-Anne, was also the supervisor of my bachelor thesis. Jan-Anne played an important role by helping me set up a clear structure of the report, I also appreciated the calmness he exudes.

Besides my supervisors, I would like to thank Eline, a fellow graduate at TNO, for making me feel quickly at ease at TNO. I would also like to thank my study friends whom I have known since the first year of the bachelor, Claudia, Anniek, Tamar, Sarah and Merit, for the insights and frustrations I was able to share with them about the graduation process. Additionally, I would like to thank the friends I got to know in my master, Robin, Olivier, Tom & Puck, for the fun conversations in Project Room 2 where we frequently worked on our thesis together and motivated each other to be there every day. I would also like to thank my mother for the mental support during the process, although she often hardly had a clue what I was doing in terms of content, it helped me to share my thoughts about the process. Finally, I would like to thank Daan, for his help in reading through my entire thesis and providing me with feedback. In addition, I would like to thank him for all the support during the process of writing my thesis.

Contents

1. Introduction

The population of overweight people has increased significantly over the past decades (WHO, 2021) and half of the Dutch adult population was overweight in 2020 (CBS, 2020). Being overweight equals a body mass index (BMI) that reaches or exceeds 25 (WHO, 2020). Excessive weight not only results in higher costs for society but also causes a reduction in the quality of health-related aspects of life. Examples are increased risks of cardiovascular disease, type 2 diabetes, and various forms of cancer (Hecker et al., 2022). In addition, it affects our mental state and can lead to stress and depression (Simon et al., 2006).

There are several causes of being overweight. More and more research is focusing on the underlying causes of the rapid growth of the overweight population and the role of environmental factors (van Erpecum et al., 2022; Williams et al., 2015). On the one hand, it appears that Dutch people with lower socioeconomic status are more likely to develop an unhealthy weight status (Hulshof et al., 2003; Van Lenthe et al., 2004). On the other hand, environmental factors such as the food offerings have a prominent influence on our eating behavior (J. Seidell, personal communication, May 19, 2022). No longer can individual determinants be identified as the only cause of the problem because we live in a so-called 'obesogenic environment' that encourages us to consume unhealthy or excessive food and in which exercise is not stimulated (Mackenbach, 2016). The problem is also characterized by several uncertainties, an example of which is the development of the unhealthy environment in the neighborhood.

The Dutch healthcare system is known for its good quality and has long been represented in the top three of the Euro Health Consumer Index since 2005 (Björnberg, 2016). The life expectancy of Dutch citizens is high and healthcare is accessible and affordable for everyone. However, there is a downside, healthcare is becoming more expensive and amounted to 80.9 billion euros in 2019, accounting for about 10% of GDP (CBS, 2020).

General practitioners are of great importance within the Dutch healthcare system because they are the first point of contact for patients. As a result, specialist care is only provided when needed. In 2018, the Dutch government delegated responsibility for public health related tasks to municipalities partly with the aim of achieving an integrated approach between different professionals in the field. A wide range of stakeholders are involved, including general practitioners, food providers, patient organizations, community sports coaches and insurers (Ministry of Health, Welfare and Sport, 2018). In recent years, the importance of combined lifestyle intervention and the collaborative approach between different stakeholders for a more personalized coaching program to reduce overweight has been highlighted (Brink et al., 2022). Insurers are important for the policy given their role as funders. At the same time, patients and patient organizations have become important partners in the policy making process. An example of this stakeholder is Patient Federation Netherlands which represents about 200 patient and consumer organizations (Patiëntenfederatie Nederland, n.d.).

Since 2015, the 380 municipalities have been responsible for implementing health policies. Since then, many local initiatives have been initiated of which some of them are still running, such as Je Leefstijl Als Medicijn (n.d.), 2diabeat (n.d.) and JOGG-Zaanstad (n.d.). Another example is the New Roads project, in which the elderly are encouraged to walk more (Storm et al., 2018). Although these initiatives provide insight into the effectiveness of projects, it remains ex ante unclear which health promotion program and which combination of programs is relevant and most effective over time in a specific neighborhood given its individual and local character.

Several studies have attempted to uncover the factors in neighborhoods that influence the development of overweight in the population (Lakerveld et al., 2012; Seidell et al., 2021). However, according to Storm, Post, Verweij, and Leenaars (2019), it remains difficult for Dutch municipalities to halt the growth of the population of overweight people in their region, and new ways of local policy support are needed.

Since 2015, researchers at the Netherlands Organization for applied scientific research (TNO) are investigating which factors influence the process of gaining weight on the individual level from a complex systems view (van Wietmarschen et al., 2018; van der Valk et al., 2019; Brink et al., 2022), see Figure 1.1. Different versions of so-called causal loop diagrams (CLDs) of overweight were developed in which the factors and their mutual causality are mapped. Since 2021, TNO works together with Partnerschap Overgewicht Nederland (PON) to develop an integrated web application to integrate social and health care professionals for effective, more personalized prevention and treatment of overweight adults. Municipalities in the Netherlands are involved as fieldlabs, i.e. environments in which policy options are explored and tested (Partnerschap Overgewicht Nederland, 2021). Within the TNO-Project PON Overweight Network Approach, the system thinking approach allows the researchers, professionals and policymakers to look at the system from a broad perspective, including influences on an individual, financial, food, physical, mental and environmental level (T. Sluijs, personal communication, December 16, 2021). Some of these factors are also neighborhood-dependent. Neighborhoods differ in terms of e.g. number of citizens, socioeconomic status, food supply, culture and political view of local policy makers. Every neighborhood is different in terms of food supply, number of citizens, local health care, culture and local policy makers. As a result, the combination and impact of factors that play a role in the problem are different in each neighborhood, and needs to be taken into account in policy advices.

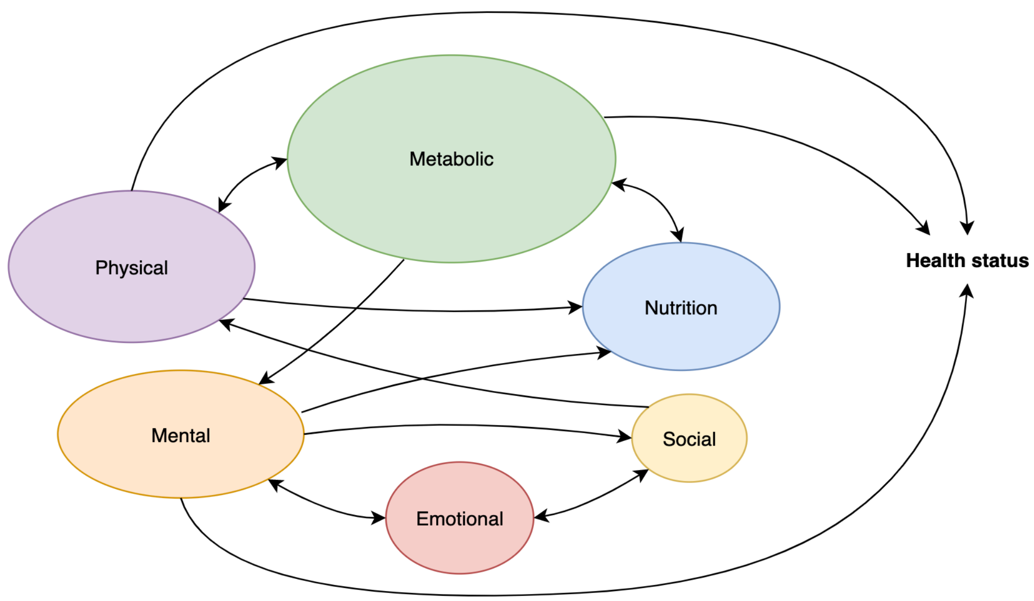

Figure 1.1 Simplified CLD diagram of the influence of health-related domains on one another and the health status

Note. Adapted from "Developing a Personalized Integrative Obesity-Coaching Program: A Systems Health Perspective", by Brink, S. M., Wortelboer, H. M., Emmelot, C. H., Visscher, T. L., & van Wietmarschen, H. A., 2022, *International journal of environmental research and public health, 19(2).* p. 5.

1.1 Research problem

The problem which is central to this thesis is that it is unclear how to reduce the degree of overweight in a neighborhood efficiently. Although neighborhoods differ, in every neighborhood, most of the scientifically mentioned causes related to being overweight apply but the question is to what extent and how they relate. A synthesis of the scientifically mentioned factors related to weight gain and their impact in a specific neighborhood is lacking. As a result, it is unclear to local policy makers in what direction and how they could steer to reduce overweight in their own neighborhood most efficiently.

1.2 Research objective

This research responds to the research problem by combining the knowledge acquired to date on the subject in order to provide ex ante policy advice for combating overweight in the neighborhood. A simulation model will be built in which the possible effects of factors that influence overweight are quantified and brought together. This model is subjected to several possible policy interventions which are tested under different possible future situations. Possible future situations relate to aspects involved in the problem whose contribution is uncertain, such as the degree people engage in sport activities or for which it is uncertain how it will evolve in the future, such as developments in the food environment.

The goal is to give policymakers insights about current factors determining overweight in their neighborhood and to provide insights in the effect of local interventions aiming at reducing adult overweight. The integration of knowledge could also contribute to the development of a policy decision support tool that links all the findings together for a neighborhood-specific understanding of the problem.

1.3 Scientific and societal relevance of the study

There is an extensive amount of research that provides insight into a variety of demographic, biological, cultural, economic, social, and environmental determinants of weight gain (Hulshof et al., 2003; Verdonk & van Koperen, 2007; van Erpecum et al., 2022). Some studies focus primarily on a single or a few number of aspects that are underlying causes of excessive weight. A growing body of literature examines the interrelated impact of various determinants (Romieu et al., 2017, Van Wietmarschen et al., 2018; Van der Valk et al., 2019). Given the complexity of causes of the increase of the overweight population, a systems-based approach is considered helpful because it allows feedback structures and interdependencies to be examined (Brownson et al., 2017). Several system modeling techniques have been applied to capture underlying mechanisms that influence the growth of people with excessive weight, including so called agent based models to examine factors of impact among the English adult (El-Sayed et al., 2012) and the American youth (Hammond & Ornstein, 2014) populations. These agent based models allow quantitative information on the problem but fall short in providing insights in factors of impact regarding the Dutch population. In addition, agent based models are useful for providing insight into factors determining overweight on an individual level given their setup but are less useful for providing information about a higher level of aggregation, like neighborhoods. After reviewing several studies with systems approaches regarding this topic, Morshed et al. (2022) point out that previous models mainly focus on personal determinants and they address an important gap in the literature namely the exploration of governance determinants and macro-level determinants.

In the Netherlands, Waterlander et al. (2021) investigated the behavior of youth related to obesity using a CLD. The model Individual Overweight model established by TNO using a system approach provides insight of factors affecting overweight in adults in a qualitative manner (T. Sluijs, personal communication, 16 December, 2021). This model offers a representation of which determinants play a role but cannot be deployed for specific policy recommendations because quantitative information is lacking. Up until now, no simulation model has been established to provide insight into determinants influencing overweight on a neighborhood level in the Dutch population.

The scientific contribution of this research comes from applying and combining current knowledge in a simulation model to create new insights. This model has the potential to 1) capture the whole subject by establishing the quantitative relationships of the factors proven to have an impact, and 2) simulate the possible effects of potential local policies on overweight in the neighborhood. By approaching the problem using a simulation model the complexity of the problem can be identified, and new insights are gained into the situation regarding overweight in a specific neighborhood. In addition, long-term effects of (a combination of) policy interventions on a local scale can be examined in more detail by means of model simulations using local data.

The societal contribution is given by creating more awareness of the complexity involved and providing policy advice that has the potential to counteract overweight in the population. By providing policy makers with robust advice based upon easy accessible computer simulation experiments, more clarity is created about the neighborhood situation and reduction of overweight can possibly be effectively addressed at the local level.

1.4 Main research question

To give local Dutch policy makers and healthcare professionals more insight into the effectiveness of (combined) policy measures, a systems thinking approach to the issue that exposes the factors influencing the problem on a neighborhood level and their impact on different subgroups, could offer new opportunities. In addition, given the uncertainty of certain factors, more information is needed about the effect of multiple policy measures in different scenarios. A policy intervention is considered robust if it can approach overweight in an economically and socially sustainable way and if the individuals it targets are positive about the method. The following research question will be addressed in this research:

What combination of local policy interventions can be deployed to reduce overweight at the neighborhood level?

1.5 Scope of the study

Increases in the overweight population occur on a global scale. There is a wide variety of aspects from different domains that influence the problem, and these aspects are partly country-dependent (Popkin & Gordon-Larsen, 2004). This thesis builds on the CLD of TNO in which individual determinants of overweight and obesity of adults in the Dutch population have been established (Partnerschap Overgewicht Nederland, 2021; T. Sluijs, personal communication, December 16, 2021). The Dutch population is therefore the focus of the present study.

A neighborhood-oriented approach was chosen, for two reasons. First, a combined approach of specialists is considered advisable (Brink et al., 2022). Often these specialists such as general practitioners and physiotherapists operate at the neighborhood level. In addition, nowadays municipalities are also responsible for tackling health problems in the neighborhood, given decentralization of tasks by the national government (Ministry of Health, Welfare and Sport, 2018). Insight into the factors that influence overweight in municipalities is therefore relevant. Moreover, the process of weight change between children and adults differs (Epstein et al., 1995). The CLD of TNO has adults as its focus and therefore the current study will also be limited to adults.

The Schildersbuurt in The Hague is taken as a sample neighborhood for data input to the model. On the one hand, this is due to the fact that there is a long track record of collaboration between TNO and health care professionals in The Schildersbuurt and a relatively large amount of data available on this neighborhood (Gemeente Den Haag, n.d.; H.M. Wortelboer, personal communication, May 3, 2022). Also, an analysis of this neighborhood is relevant given the high proportion of overweight people in this neighborhood (Gemeente Den Haag, n.d.). The model built for this research may serve as a basis for analyzing the problem in other neighborhoods. To examine the effects of policy interventions, the model in this study focuses on simulating the degree of overweight in the neighborhood for the future five years.

1.6 Structure of the report

Chapter 2 will elaborate on the methodology used for this research. Thereafter, chapter 3 will provide a conceptual description of the system. Following that, chapter 4 connects qualitative values and relationships to the conceptual model discussed in chapter 3. Chapter 4 also provides insight into the reliability of the model. In chapter 5, the model created serves as an application for policy interventions whose effects are measured through experiments. Finally, chapter 6 provides a conclusion to the research question, the limitations of the study and recommendations for further research.

2. Research approach and methodology

This chapter discusses the methodology applied to answer the research question. The first section describes the approach used to find a suitable method. The second section explains the content of this method. The scientifically associated research design to this method and the sub-questions belonging to the main question are described in the last section of this chapter.

2.1 Research approach

It is uncertain how the number of overweight people will develop over time. The problem encompasses many non-linear factors, such as physical activity, mental resilience, and use of fast-food products (van Erpecum et al., 2022; Williams et al., 2015). The Ministry of Public Health has encouraged municipalities for several years now to implement integrated health policies (Steenbakkers et al., 2010). The national government has also drawn up a national prevention agreement in 2018 (Ministry of Health, Welfare and Sport, 2018) that focuses on the local reduction of health problems including overweight partly because of the desired intersectoral collaboration. Although policymakers have made efforts in the past to reduce the overweight population, the proportion is still growing every year (RIVM, 2020; NOS, 2022) so it can be argued that previous policy measures have not had the desired effect. Local policymakers are expected to commit to addressing the problem given the societal impact it causes and the integrated approach that is needed, but according to PON it is difficult to determine which policies are effective (Wortelboer & Sluijs, personal communication, November 4, 2021).

Given that “a policy model may be used to explore a policy option, helping to identify and specify in detail a consistent policy design” (Gilbert et al., 2018, p. 2) a modeling approach is suitable to explore which policy interventions are suitable to effectively reduce the degree of overweight in the Dutch population. The model is therefore not an answer in itself, but contributes to insight into the system, allowing experiments with different alternatives and the results of each as a basis for recommendations (Gilbert, Ahrweiler, Barbrook-Johnson, Narasimhan, & Wilkinson, 2018).

2.2 Modeling technique

From section 2.1, a modeling technique was found to be suitable. This section reviews the available modeling techniques and identifies which one is appropriate for this problem. This is followed by a more in-depth consideration of the chosen method.

2.2.1 Exploration of modeling techniques

Several modeling methods are suitable for simulating, such as agent-based modeling, system dynamics (SD), and discrete simulation. Agent-based modeling focuses on simulating the actions of agents and mutual interactions (Macal & North, 2009). The agents in this method are autonomous decision-making bodies and collectively the agents in the model represent the system (Bonabeau, 2002). For the current study, these agents would involve individuals.

SD is a method developed by J.W. Forrester (1958) in which dynamic and complex processes, which are characterized by the influence of existing conditions on the system, subsequently modify certain model conditions and thereby trigger later changes, can be modeled. These conditions are also known as feedback structures. SD is applied to investigate a system that is complex and dynamic in nature (Nieuwenhuijsen et al., 2018). In Discrete event simulation (DES), events in the system are simulated as a sequence of activities over time. Individual entities are in the same state for a specified period of time and this state changes on the occasion of a discrete event (Hild, 2000).

There are some important differences between the three modeling techniques. Agent based modeling approaches a problem at the micro level, while system dynamics focuses on a higher level of abstraction to the problem at the macro level. SD has also been criticized for its macro level perspective because it does not provide insight into micro-scale behavior and if this knowledge is lacking, the entire system could not be fully understood (Ding et al., 2018). However, agent-based modeling is less suitable for the scope of this research, as the emphasis is not on the behavior of the individual. In discrete simulation, the state changes of the system are progressed at discrete times. This modeling technique mainly serves to answer specific questions, for example at the operational level (Brailsford & Hilton, 2001). Within this study, the aim is to gain insight into the complex system and the relationships between different elements, making SD modeling more suitable than discrete simulation.

Another advantage of the SD method is that it allows to estimate and simulate unforeseen interactions and understand their consequences so that outcomes of policy interventions can be tested on possible emerging situations (Marshall et al., 2015). Adding to that is the fact that SD is suitable for gaining insight into long-term effects (Pruyt, 2013) which enables insight into the effectiveness of measures aimed at combating overweight in the long term.

A limitation of SD simulation is the fact that it uses a continuous dimension in which the number of overweight people in the model is represented as non-integer numbers, which of course would not be possible in reality. However, it does provide a way to experiment with possible future scenarios and allows for well-considered policy considerations (Sterman, 2001).

Given the above arguments, SD modeling is considered suitable for the analysis of the problem.

2.2.2 Methodology

Systems thinking is a discipline that focuses on the structure that causes behavior. Previously, Seidell et al. (2021), encouraged research based on systems thinking. As previously highlighted, agent-based models were used to map neighborhood-level overweight factors for the English and American populations (El-Sayed et al., 2012; Hammond & Ornstein, 2014). Regarding SD models specifically, within the health domain, particularly on the topic of obesity-related causes and the effectiveness of interventions, there has been some research. Chen et al (2018) used an SD model to conduct exploratory research on the effectiveness of economic interventions to reduce obesity in the United States. And the role of portion size on becoming obese was examined by Abidin, Zulkepli, & Zaibidi using an SD model. Recently, TNO developed a SD model that provides more insight into the various factors that play a role in the patient pathway in diabetes and addresses the outcome of lifestyle interventions on the social costs related to this disease (Sluijs, 2021). A systems approach and more specifically an SD method thus appears to be appropriate for this type of issue.

The underlying feedback loops that cause actions are included in the system thinking analysis rather than just studying an individual action. Haraldsson (2000) describes this concept well with the example of filling a glass of water. The intentions described in Figure 2.1a and 2.1b are the same but there is a difference in the process of traditional linear thinking and systems thinking.

Figure 2.1a Traditional linear thinking example

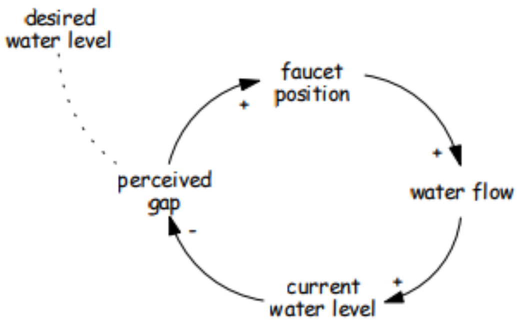

Figure 2.1b Systems thinking example

Note. Reprinted from "Introduction to systems and causal loop diagrams", by Haraldsson, H., 2000, System Dynamic Course, Lumes, Lund University, Sweden. p. 19.

By reasoning from a systems thinking perspective underlying causes of certain behavior can be observed and insight can be gained into the aspects one can influence to change system behavior (Haraldsson, 2000).

SD centers on the utilization of information feedback and state variables concepts in an effort of modeling social systems and studying the connection between the structure of the system and its behavior over time. Behavioral changes in the model originate from the structure of the model. These changes underlie shifts in dominance among various feedback loops that involve processes of non-linearities, delays, and accumulation (Forrester, 1968a, 1968b).

Examples of feedback structures in this study concern the reinforcing loops between overweight and physical activity and between active transport and inactive transport. The structure of a system dynamics model is based on the presence of stocks and flows (Forrester, 1994). In which stocks are used to bring objects or people into view, such as the number of people who are overweight. Flows can be perceived as the process of a transition of the object from one phase to another such as the process whereby an overweight person loses mass reaches a healthy weight and thereby ends up in the stock of people with a healthy weight.

The process of system dynamics modeling is divided by Forrester (1968) into five stages: problem identification (1), model conceptualization (2), model formalization (3), model testing (4), model use (5). These phases will be completed in this thesis and therefore the content of each phase will be explained in more detail in the next section

2.3 Research design and subquestions

Experts in the field speak of different processes in which SD phases are interrelated (Forrester, 1994; Richardson & Pugh, 1981) but in any case, a highly iterative process (Pruyt, 2013). There will be a considerable amount of trial and error during the modeling process, because "modeling is iterative, a continual process of testing and revision, of both formal and mental models" (Sterman, 2002, p.28). The steps distinguished in the SD process by Forrester (1968) are applied as a reference in this thesis. Throughout the research phases, sub-questions will be addressed that together formulate an answer to the main question. To answer the subquestions, different research methods were used. The research phases, research methods and sub-questions can be defined as follows;

1. Problem identification

In the first step, the problem that is central to the research is articulated, which according to Sterman (2000) is also the most important step in the process. The main issue should be distinguished from the side issues and the purpose of the model should be explained. Without a clear purpose it will be difficult to conduct a proper modeling study. Modeling is all about understanding which aspects to include and which not to include, and a clear purpose contributes to this knowledge. The focus of the model should be on modeling a problem and not a system. When the focus is on a system, the model will have to include an excessive amount of variables to answer all conceivable questions. So, in this step the boundaries of the model are determined by describing 1) the factors that are relevant for the consideration of the problem and therefore should be included and 2) the irrelevant factors relevant factors that can be excluded (Sterman, 2000). A partial description of the problem has already taken place in the introduction of chapter 1. The next chapter will continue with an outline of the boundaries of the model. In doing so, existing (scientific) literature is consulted. The first subquestion is central during this phase;

- **SQ1**: What are local biological, social, economic, demographic and environmental factors that influence the development of overweight in a neighborhood?

2. Model conceptualization

The next step in the modeling process involves the conceptualization phase. Sterman (2000) also refers to the creation of a dynamic hypothesis. By this he means the description of a theory that can explain the problematic behavior. The term dynamic comes from the nature of the system, consisting of feedback structures, stocks and flows. The problem is approached from different perspectives in this phase and the main accumulations (stocks) are determined (Martinez-Moyano & Richardson, 2013). CLDs and stock and flow diagrams (SFD) play an important role in this phase given their ability to represent the structure of the system including feedback mechanisms (Khan et al., 2016). The use of both a CLD and SFD is justified and a combination of both is even encouraged (Martinez-Moyano & Richardson, 2013). Therefore, in this thesis the main stocks and flows are implemented in a CLD diagram in the conceptualization phase. The causal loop diagram of overweight developed by TNO within the TNO-Project PON Overweight Network Approach provides insight into factors related to overweight on an individual level and was taken as a basis. Scientific literature on cultural, demographic, environmental, economic and social level were retrieved to gain insights about neighborhood involved factors and their underlying causality. Additionally, an interview with health expert J. Seidell was held to obtain feedback about the constructed model. Seidell has made many contributions to research in the area of overweight determinants and interventions as well as research on the underlying causes of increasing weight at the neighborhood level (WHO, 2003; Doak et al., 2006; Seidell & Halberstadt, 2015). He has broad and deep knowledge on the subject which enables him to assess the model's completeness for achieving the objective. The sub question that will be addressed during this phase is;

- **SQ2**: What is the structure of the overweight system at a neighborhood level?

3. Model formalization

After constructing the qualitative model, mathematical equations were formulated and assigned to the parameters. Quantification of elements of the model was extracted from various data sources on national and neighborhood population level. This concerns data from sources such as the National Institute for Public Health and the Environment (RIVM), which collects data on the health of the Dutch population, and which provides insight into figures on overweight in a neighborhood. Datasets from the Dutch Central Bureau for Statistics (CBS; https://www.cbs.nl) providing data on economic, cultural, and environmental aspects were consulted as well. Sources that provide figures at neighborhood level are https://allecijfers.nl and https://denhaag.incijfers.nl, the latter of which focuses explicitly on the city of the Hague in which the Schildersbuurt is located. Examples of information available on these websites are figures on, for example, the valuation of social cohesion in a neighborhood. The quantitative model is constructed using System Dynamics software and provides the opportunity for numerical simulation of the progression of people with excess weight in the population over time. During this phase, also the assumptions made for the establishment of the model are clearly explained.

4. Model testing

In order to verify that the established model matches the intended objective of the model and can meet this objective, several tests are performed. Model testing is in principle already executed during the construction of the first formulas (Sterman, 2000). Verification and validation tests, like extreme condition test, boundary adequacy, dimensional consistency and sensitivity analysis will serve as research methods. By performing these tests, the correspondence of variables to actual concepts is checked and the reliability of the model outcomes is increased. This phase assesses the capability of the model to reflect real behavior of the degree of overweight in a neighborhood over time, so that it can be decided whether the model is able to serve as a tool for experiments with policies.

5. Model use

After the model is established and its confidence is enhanced, it can serve as a tool for evaluating policy interventions. According to Sterman (2000) “the robustness of policies and their sensitivity to uncertainties in model parameters and structure must be assessed” (p. 104). Therefore, uncertainties in the model will first be assessed for their impact on model behavior using an uncertainty analysis where variables are tested for their sensitivity. Unlike sensitivity analysis, the focus is not on testing the explainability of the model behavior for small changes in input values, but the impact of these changes on the system is the focus. Next, in order to select potential policies, studies and reports on existing projects and initiated ideas will be consulted and assessed for their effectiveness. The chosen policies will then be discussed and then evaluated using the simulation model under the possible uncertainties that may arise. The last two sub questions will be addressed during this phase which involve;

- **SQ3**: What are measures that can be deployed by local policymakers to tackle overweight in this neighborhood?
- **SQ4**: What are the possible effects of these policies on the system under different uncertainties?

3. Qualitative modeling of overweight on neighborhood level

This section provides a description of how the determinants of overweight relate to the system by using a qualitative approach. First, the definition of overweight will be given in section 3.1. The approach of the qualitative analysis is described in section 3.2. The chapter ends with the conclusion in section 3.3.

3.1 Definition of overweight

In people of healthy weight, there is a balance between dietary intake and their metabolism. The energy balance formula is shaped by the difference between human energy intake and energy consumption. Excess weight is caused by an energy imbalance where energy intake exceeds energy consumption (Hill, 2006; Fallah-Fini et al., 2021). A positive energy balance for an extended period of time results in the storage of fat in the body (Sari & Wijaya, 2017).

A person's Body mass index (BMI) provides insight into the ratio of weight to height (kg/m^2). The World health organization (WHO) (2000) has established BMI values for classifying different weight groups, such as underweight and overweight. People with a BMI between 25 and 29.9 kg/m^2 are labeled as overweight. The term obesity is used when someone has a BMI that is higher or equal to 30. Within obesity, several types can be distinguished such as obesity class 1 (BMI between 30 and 34.9 kg/m^2), obesity class 2 (BMI between 35 and 39.9 kg/m^2) and obesity class 3 (BMI above 40 kg/m^2) (WHO, 2000). The use of BMI as a method has been criticized for its shortcomings, for example, it does not take into account muscle mass or differences between races (Müller et al., 2016; Prentice & Jebb, 2001). Nevertheless, it is a widely used method because it has coherent findings with important health outcomes (Nuttall, 2015). The focus of this study is on the overweight population. The current model does not include any further classifications besides overweight, so when talking about this population group it refers to all people with a BMI above 25 kg/m^2.

3.2 System boundary

According to Sterman (2000), one of the most difficult parts of system modeling involves determining the system boundary. The model's purpose serves as a guide here so that only the essential features to meet the objective are included. The objective of the current study focuses on identifying the aspects in a neighborhood that contribute to becoming overweight. The Key Performance Indicators (KPIs) of the study hence concern the number of *people with overweight* and the *percentage of overweight people in the neighborhood*. A system with a boundary that is too wide will never be able to be fully modeled. As Mihailo Mesarovic, developer of global simulations, once said "No matter how many resources one has, one can envision a complex enough model to render resources insufficient to the task" (Meadows et al., 1982, p.136-137). As previously shown in the literature and in TNO's CLD on overweight, there are an incredibly large number of factors and interactions involved in this issue. Given time constraints, the study therefore focuses primarily on identifying key mechanisms, because as Sterman points out; "a broad model boundary that captures important feedbacks is more important than a lot of detail in the specification of individual components" (Sterman, 2000).

Within system dynamics, attempts are made to determine behavior endogenously, meaning that it is determined within the system. Exogenous variables are those that are outside the boundaries of the system. Only a small number of exogenous variables should be included in the model (Sterman, 2000).

The domains from which the problem of local overweight can be approached concern biological, health, physical, nutritional, social, economic, demographic, environmental and political perspectives. Factors from these different domains are included in the study because they are interconnected and thus together influence the complexity of the system. Being overweight is caused by unhealthy lifestyle of overeating and not exercising enough. On the one hand, there is a biologically regulated aspect, thermogenesis aims to balance intake and expenditure (J. Seidell, personal communication, May 19, 2022). To a large extent, a healthy lifestyle is influenced by factors external to the body, such as the food environment (Mackenbach, 2016), socioeconomic status (Roy et al., 2015), addictions (Filozof et al., 2015), social environment (Verdonk & van Koperen, 2007), age and ethnicity (Nicolaou, Nierkens, & Middelkoop, 2013). These factors are important for neighborhood-specific assessment of overweight levels over time and are therefore within the scope of the current study. Diseases related to overweight lie outside the scope of this thesis. The amount of green space in the neighborhood is excluded from the scope of the study because it is not considered an impactful factor (Den Hertog, 2006). Economic factors at a high, national aggregate level, such as healthcare costs are outside the scope. This also applies to politics at the national level. The exact variables that are endogenous, exogenous, and outside the scope of the study are extensively described in appendix A.

3.3 Qualitative analysis approach

Goal of this section is providing insight into the functioning of the system by representing the key elements in a conceptual version of the model. Within systems thinking, CLDs and SFDs are used to structure a problem. A combination of the two is encouraged (Martinez-Moyano & Richardson, 2013) and was developed during this study. The features of causal loop diagrams are explained in Figure 3.1a and this mental model allows for the mapping of circularity of aspects in the problem. In this way, it allows for the analysis of system behavior (Haraldsson, 2000). Figure 3.1b shows the meaning of the concepts used in SFD diagrams.

Symbol	**Meaning**
Arrow Tail → Head	The arrow is used to show causation. The item at the tail of the arrow causes a change it the item at the head of the arrow.
→ +	The + sign near the arrowhead indicates that the item at the tail of the arrow and the item at the head of the arrow change in the *same* direction. If the tail *increases*, the head *increases*; if the tail *decreases*, the head *decreases*.
→ –	The – sign near the arrowhead indicates that the item at the tail of the arrow changes in the *opposite* direction. If the tail increases, the head decreases; if the tail decreases, the head increases.
(–) or (–)	This symbol (also B), found in the middle of a closed loop, indicates that the loop continues going in the same direction, often causing either systematic *growth* or *decline*, behaviour that unstable moves away from equilibrium point. This is called a *positive feedback loop* .
(+) or (+)	This symbol (also R), found in the middle of a closed loop, indicates that the loop changes direction, causing the system to *fluctuate* or to *move toward equilibrium* . This is called *a negative feedback loop* .

Figure 3.1a Summarized explanation of the causal loop concept

Note. Reprinted from "Introduction to Computer Simulation: The System Dynamics Approach", by Andersen, D., Roberts, N., Deal, R., Garet, M., & Shaffer, W. D., 1983. p. 56.

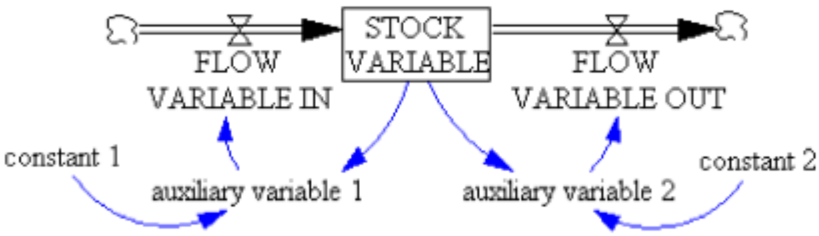

Figure 3.1b Concepts in quantitative SD modelling

Note. Reprinted from "Small system dynamics models for big issues: Triple jump towards real-world complexity", by Pruyt, E., 2013. p. 86

The qualitative approach captures the process of constructing the conceptual model. As Pruyt (2013) pointed out, building a model is an iterative process and it is best to start with a small model, test it, and incrementally expand with other submodels. To do so, the following steps were taken:

- Identifying the sub models
- Establishing the individual sub models
- Connecting the individual sub models
- Identifying feedback loops
- Combining the submodels and feedback loops into a CLD

3.3.1 Identifying the sub models

Overweight occurs as a result of excessive adipogenesis, a biological process referring to the development of fat cells (Lefterova & Lazar, 2009). The production of these fat cells, adipocytes, occurs at the cellular level (Rosen et al., 2000). Analyzing the development of the development of overweight in the population over time concerns yet another branch of the subject. No longer the individual but the entire population is the central focus and thus it concerns a macro-level analysis. As Forrester (1980) describes, by using all kinds of different data it is possible to expand from the micro level to the macro level. In order to model the amount of overweight people, a macro level perspective, the aspect of weight gain at the meso level is taken as a starting point. As shown in the definition of overweight, an energy imbalance lies at the basis of its occurrence (Hill, 2006; Fallah-Fini et al., 2021) and the model is therefore established using this mechanism. The energy imbalance concerns unbalanced values of the intake and expenditure of energy in the body, where a disruption between the two triggers a storage of excess fat (Sari & Wijaya, 2017). Based on this information, three sub-models for this model were created, concerning energy consumption, energy intake and the degree of overweight in the population. The sub models of expenditure and intake are measured on an individual, meso level and averages of these values represents the population. The population variable is thus an important variable for the establishment of other elements in the model. The sub model of degree of overweight is on a macro level. These three sub models together have the ability to simulate the number of people who are overweight over time.

3.3.2 Establishing the individual sub models

After establishing appropriate sub models the qualitative approach continues with investigating the structure of those individual aspects. There are a variety of biological, economic, social, cultural, and environmental aspects that influence both energy intake and expenditure (Williams et al., 2015). TNO's

Causal loop diagram provides insight into factors from such sub-domains. Based on research with experts from all kinds of related domains they established a CLD with mental, nutritional, financial, individual, environmental and drug related determinants (T. Sluijs, personal communication, December 16, 2021). Actions by local healthcare providers were implemented in the model in order to gain insight into the mechanism they affect. This diagram along with reports and literature reviews contributed to the establishment of the three sub models.

Sub model 1: Total energy expenditure

There are several ways in which the body consumes energy. The sub model of total energy expenditure was established based on the physiological mechanisms responsible for it. Those mechanisms can be divided into three main aspects; resting metabolic rate, activity thermogenesis and food-induced thermogenesis (Donahoo et al., 2004; Westerterp et al., 1999).

The largest of these three components is the resting metabolic rate, with a share of 60-70% of total energy expenditure (Swaen et al., 2005; Snitker et al., 2001). It is the energy expended during rest and concerns all energy consumed for self-maintenance of the body (Burton et al., 2011). Different values of resting metabolic rate between individuals are determined by difference in body composition, among other factors (Frankenfield et al., 2005). The food-induced thermogenesis is the energy consumed during the digestion of food and accounts for approximately 10% of the total and is considered a fixed proportion by most researchers (Hills et al., 2014). The third component of total energy consumption is active thermogenesis. It is the energy used during daily activities and sport. Within this form of thermogenesis, a distinction is made between exercise-related thermogenesis and non-exercise related activity thermogenesis, of which the latter occurs during a variety of daily non-sport related activities and exercise related activity thermogenesis which occurs during planned sporting activities (Melanson, 2017; Von Loeffelholz & Birkenfeld, 2018). As a result, non-exercise related activity thermogenesis and exercise-related activity thermogenesis has also been distinguished in the conceptual representation of sub model 1, as shown in Figure 3.2.

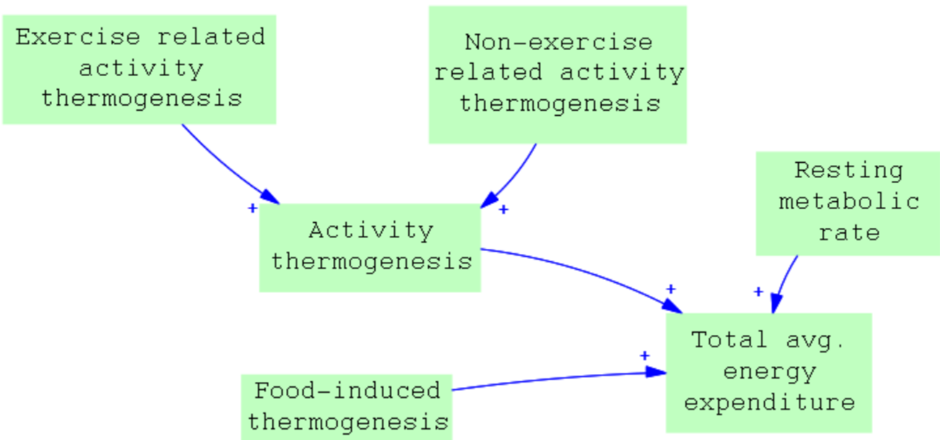

Figure 3.2 Aggregated representation of submodel 1 describing the total average energy expenditure of an individual in the Neighborhood Overweight Model

Sub model 2: Total energy intake

Energy is indispensable for the processes and activities described in the previous section to which our bodies are subjected on a daily basis. This energy is derived from nutrients in foods and drinks.
Various studies show that our socio-economic status has a major influence on the food we consume,

indicated as macronutrients (fats, proteins, carbohydrates and fibers) (Drewnowski & Darmon, 2005; Mackenbach, 2016; Mohammed et al., 2019). Our socio-economic status determines our scope for spending on food, the financial stress we experience and also influences our nutritional knowledge (T. Sluijs, personal communication, December 16, 2021). These three aspects combined determine to a large extent the food we consume. In addition, in recent years it has become increasingly clear that the environment has an important influence on our food choices (Roy et al.; J. Seidell, personal communication, May 19, 2022). The so-called obesogenic environment encourages people to consume ultra-processed foods (Mackenbach, 2016). The amount of energy consumed per day is examined in the second sub-model. A distinction is made between kcal from alcohol, kcal from food and non-alcoholic snacks and additional intake resulting from having an ultra-processed diet, see Figure 3.3.

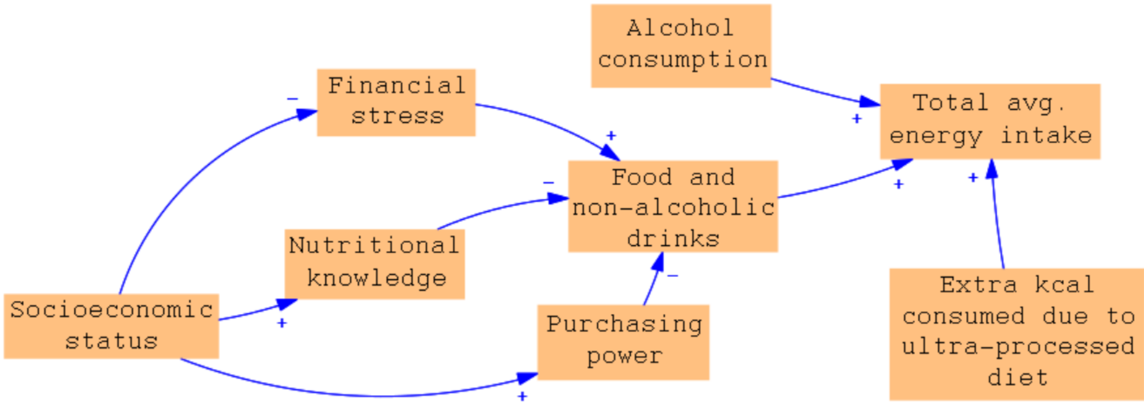

Figure 3.3. Aggregated representation of submodel 2 describing the total average energy intake of an individual in the Neighborhood Overweight Model

Sub model 3: Degree of overweight

Equilibrium in the human energy balance is obtained by equal values of energy expenditure and energy intake. A positive value of energy balance will cause fat to be stored in the body resulting in weight gain (Sari & Wijaya, 2017). The third sub-model aims to calculate how the number of kcal of energy surplus/deficit relates to the number of overweight people in the population. It includes how the average weight in the population is affected by the positive or negative energy balance. There is delay between an occurence in energy imbalance and weight gain (Hall et al., 2011), represented by the two dashes through the arrow in Figure 3.4. The average weight gain is then translated into the number of overweight people. Smoking cessation is a factor causing weight gain that is suggested to be unrelated to food intake (Rodin et al., 1987), therefore smoking is also included in the third submodel.

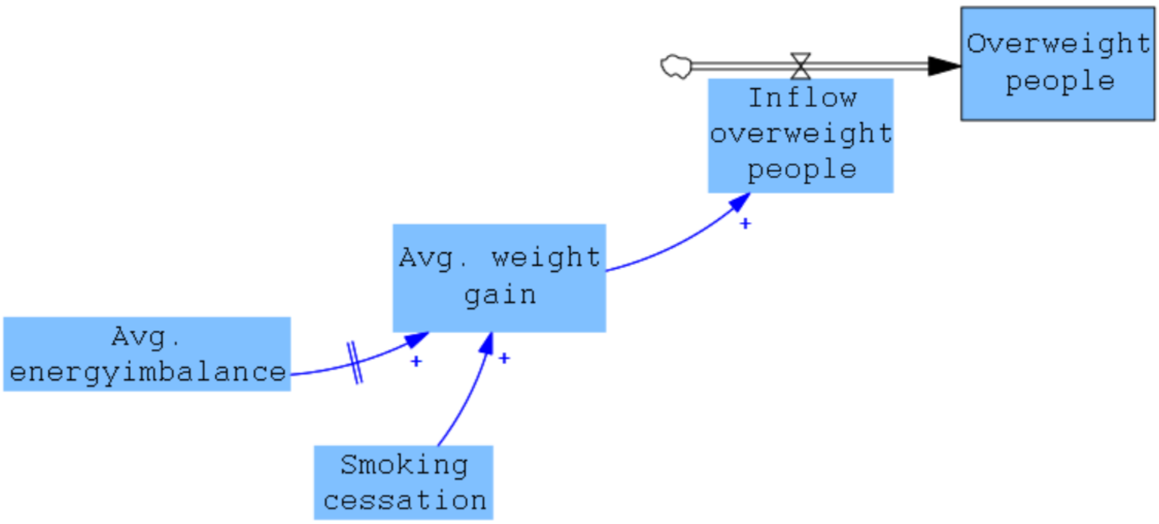

Figure 3.4 Aggregated representation of submodel 3 describing the inflow of overweight people in the Neighborhood Overweight Model

3.3.3 Connecting the individual sub models

The energy imbalance, part of submodel 3, is determined by the difference between energy intake, submodel 2, and energy expenditure, submodel 1. This means that submodel 1 and 2 are inherently related to submodel 3, see Figure 3.5. The model focuses on modeling a group of people and not individuals, therefore it is important to determine the average energy intake and energy expenditure of the population under study. From this the average energy imbalance can be determined after which a translation needs to be made to the number of overweight people within the population.

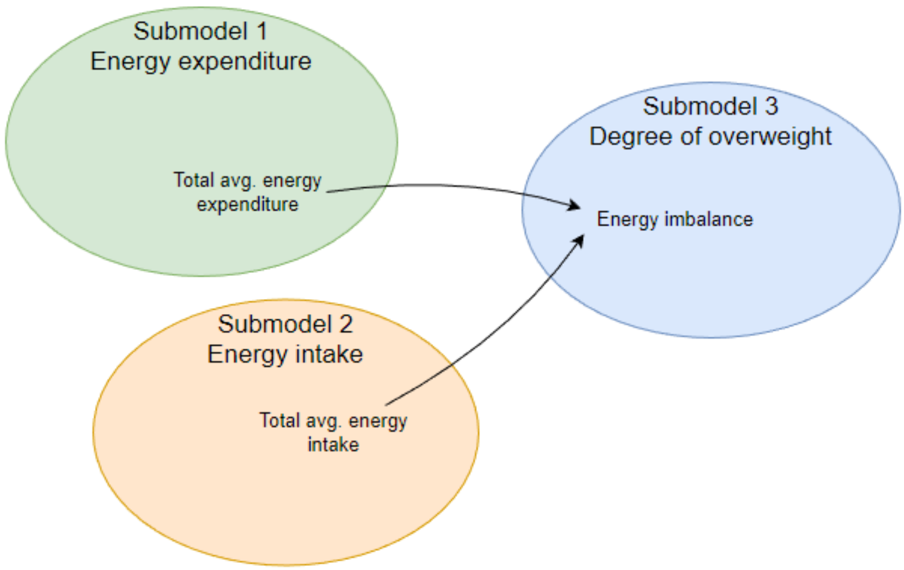

Figure 3.5 Connection of sub models 1 and 2 into sub model 3 of the Neighborhood Overweight Model

3.3.4 Identifying the feedback loops

The number of overweight people is not caused solely by exogenous factors. An essential part within system dynamics concerns the discovery of feedback mechanisms that occur in the system. There are two types of loops, self-reinforcing (positive) and self-correcting (negative). In a self-reinforcing loop, the behavior in the system is amplified. In self-correcting loops, the behavior is instead balanced

(Sterman, 2001) The occurrence of overweight in the population also amplifies or attenuates the magnitude of other variables in the model. The main feedback loops that occur in the model will be discussed in more detail in this section.

1. Activity level loops (reinforcing)

Research on the effect of physical activity on weight gain and vice versa found that excess weight has a negative effect on physical activity. The heavier a person is, the more discomfort is experienced during exercise by developing muscle problems, becoming short of breath and sweating quickly. These difficulties can reduce the motivation to be physically active and therefore the actual performance of a physical activity (Petersen et al., 2004). This leads to a decrease in the energy consumed during activity. Thus, there is a reinforcing loop here, as shown in Figure 3.6.

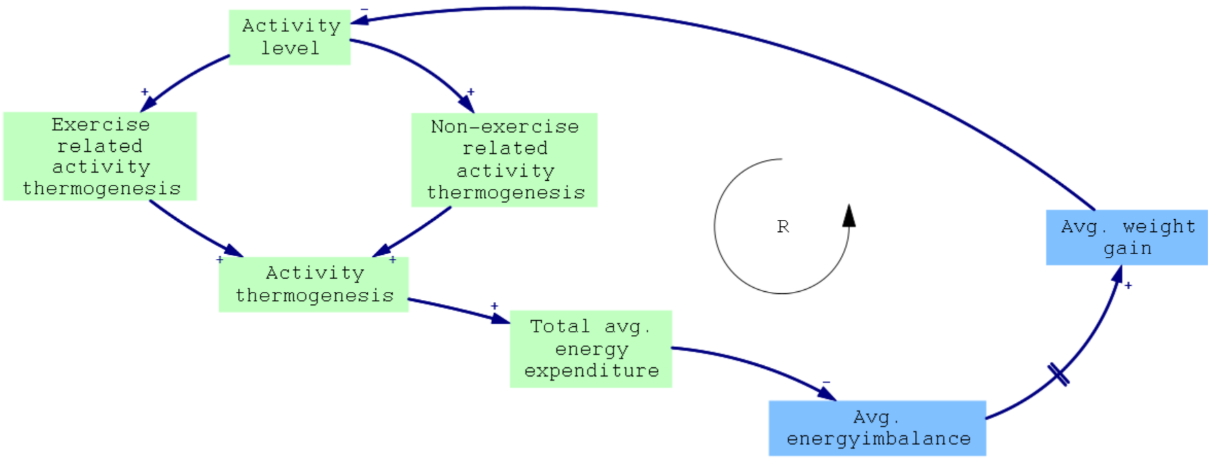

Figure 3.6. Feedback loops activity level in the Neighborhood Overweight Model (reinforcing)

2. Metabolic rate during activity loops (balancing)

On the other hand, weight also influences the metabolism, where a heavier weight leads to a higher metabolic rate (Henry, 2005; van Raaij & Groot, 2004). For example, research by Geissler et al. (1987) has shown that when subjected to the same activity, expenditure during this activity is higher in obese people compared to people of a healthy weight. These findings led to the implementation of the feedback loop in the causal relationship diagram as shown in Figure 3.7 below.

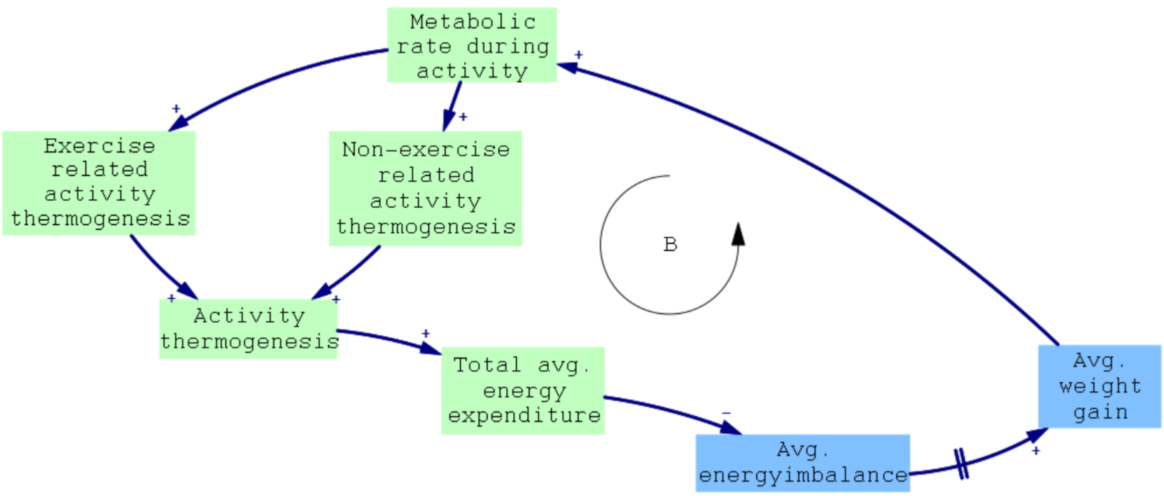

Figure 3.7 Feedback loops metabolic rate during activity in the Neighborhood Overweight Model (reinforcing)

3. Resting metabolic rate loop (balancing)

Thus, consistent with the previous feedback loop, there is also an increasing metabolism during rest with increasing weight (Henry, 2005; van Raaij & Groot, 2004) which is equated in a third feedback loop in the model, shown in Figure 3.8.

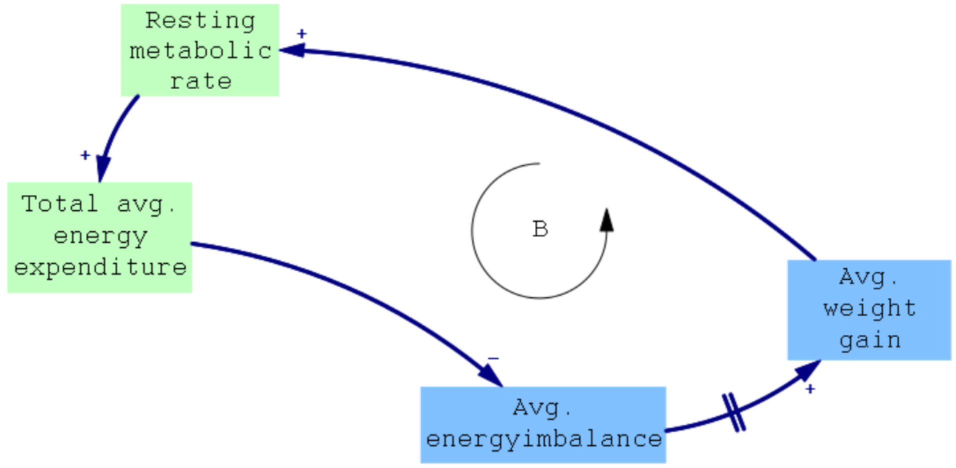

Figure 3.8 Feedback loop resting metabolic rate in the Neighborhood Overweight Model (balancing)

3.3.5 Combining the submodels and feedback loops into a CLD

An overview of the CLD with the three submodels and feedback structures combined is provided in Figure 3.9.

3.4 Summary

In the current study, all people with a BMI above 25 kg/m^2 are considered to be in the overweight population. To determine the KPIs *people with overweight* and *percentage of people with overweight in the neighborhood*, many influential factors were determined endogenously. In order to meet the objective of the model, three main sub-models are established. The first two sub-models concern energy expenditure and energy intake and together they determine the energy imbalance. The third sub-model is characterized by the determination of the degree of overweight in the population. Gaining weight occurs as a result of energy imbalance and in this way the first two sub-models are linked to the third one. The qualitative model established, in line with the nature of the system, contains three feedback mechanisms. One of these feedback structures captures the mechanisms of weight gain that influence activity level and which in turn influence weight gain, a reinforcing loop. The two balancing loops consist of the effect of weight gain on resting metabolism and metabolism during activity both of which affect weight gain again.

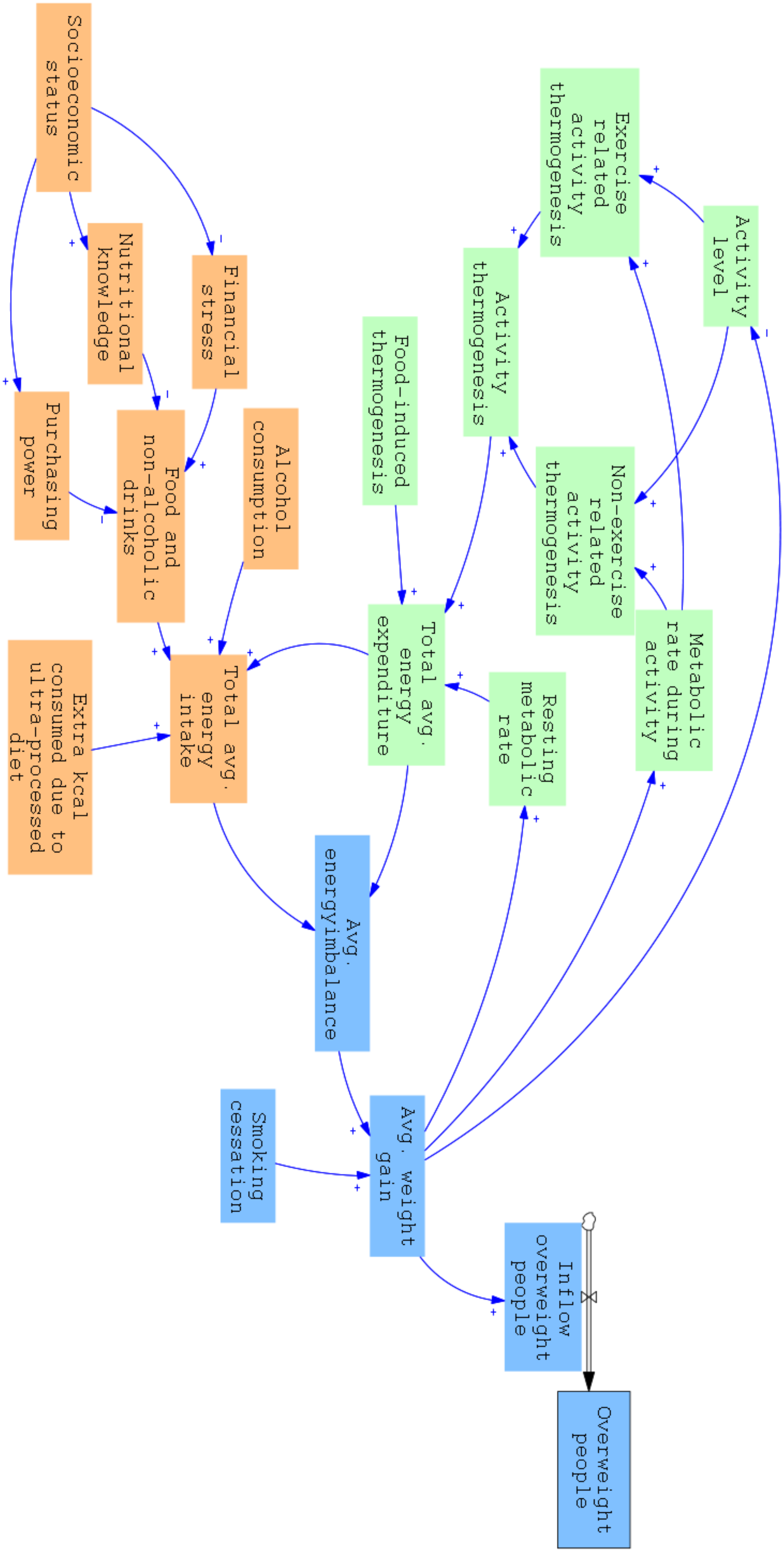

Figure 3.9 Causal loop diagram of the conceptualized system of the Neighborhood Overweight Model

4. Quantitative modeling of overweight on neighborhood level

Constructing a quantitative model of the qualitative model is the next step in SD modeling (Pruyt, 2013). The first section of this chapter explains the model formalization of all the model components. Section 4.2 follows with a discussion on reliability of the built model using verification and validation tests. In Appendix C a complete overview can be found per component representation with all the corresponding values, functions and sources.

4.1 Model formalization

This section discusses the model formalization of the model constructed in the conceptualization stage. Chapter 3 shows a high level of abstraction of the model to map the overall structure. The quantitative values of aspects at a high level of abstraction are difficult to determine because their value is determined by multiple underlying factors. Therefore, more details are needed to quantify the model. Given the size of the model, the specification of the model is divided into logical component descriptions that can be related to the submodels highlighted in the previous section.

The software program Vensim (version PRO x64) developed by Ventana Systems (Ventana Systems, Inc., Harvard, MA, USA) is used to build the quantitative model. It is one of the software programs that provides a way to simulate experiments for complex models with quantified variables. This section presents a representation of the components in Vensim and provides an explanation of the mechanisms by clarifying the parameters, stocks and flows. A variable indicated between two brackets in a lighter color (< name variable >) means that this variable is determined elsewhere in the model (and will be explained at a different part). The time unit of the model is set to days because the energy imbalance, central in this study, is measured on a daily basis and therefore many related variables are also calculated on a daily basis. Annual data of parameters is converted to daily values. Tables with the units, initial values, equations and sources of all variables occurring in the model components are provided in Appendix C.

First, it is explained how the population in the neighborhood is modeled due to the fact that the composition of the population matters significantly for several input variables of the submodels of intake and expenditure, such as socioeconomic status and walking and cycling behavior. Therefore, it is important to first consider how the population can be quantified. Next, the sub-models of energy expenditure and energy intake and their components are discussed. Subsequently, it is explained how the expenditure influences the intake. The model components related to the effect of smoking cessation on weight gain are described in the section following thereafter. Finally, the model formalization of the degree of overweight due to energy imbalance is presented.

4.1.1 Population

The composition of the population in a neighborhood partly determines the behavior of the people in that neighborhood, given that demographic characteristics such as age, gender, and ethnicity entail certain behaviors. For example, there are differences in the level of physical activity of different populations (Romeike, Abidi, Lechner, de Vries & Oenema, 2016). Age and gender are not within the scope of this model, so at the population level only distinctions will be made between different ethnic populations.

The population of ethnic groups in the Schildersbuurt is highly variable, it has already completely changed twice since World War II (Marijnissen & Zuidervaart, 2015). There has also been an increase in the number of residents in this neighborhood over the years (AlleCijfers, 2021). Both of these trends are implemented in the model with the help of so-called subscripts[1]. The different ethnic groups living in the neighborhood are modeled as subscripts to express population growth. A subscripted variable can take on multiple values for different groups. The *annual population growth* is based on the growth figures of recent years and specified for each ethnic group (in a subscript). The *change in population composition* gives the absolute number of increase of people of an ethnic group per day, on the basis of which the *people moving to the neighborhood* or *people moving out the neighborhood* can be determined. The *total population* is a sum of the population numbers of all ethnic groups together, here no distinction is made anymore between different population groups and therefore this is not a subscripted variable. Figure 4.1 provides the representation of the model version of the population aspect. Appendix C.1 provides a description of the details of the variables modeled.

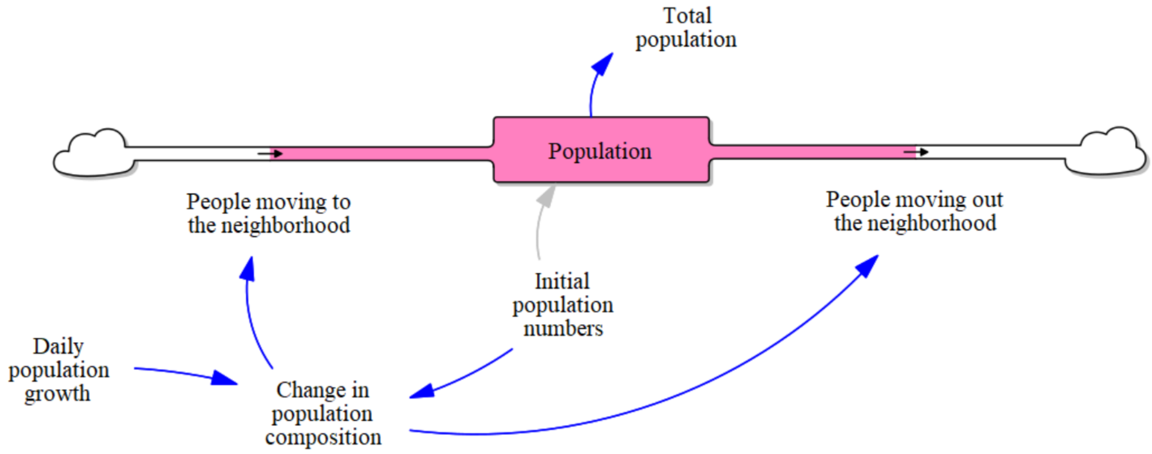

Figure 4.1 Sub model of the population in a neighborhood

4.1.2 Energy expenditure

The average total energy expenditure in the neighborhood indicates how much energy a person in this neighborhood expends on average per day, represented in the number of kcal. The *total average energy expenditure* is calculated by the separate elements of 1) average individual energy consumption during rest, 2) food thermogenesis and 3) activity as earlier explained in Chapter 3. The mechanisms of these three elements are elaborated on in the paragraphs below. The proportion of food-induced thermogenesis is considered to be a fixed proportion of 10%. For this reason, a variable of the sum of expenditure during activity and rest has been added so that this share can be multiplied by the *ratio for food-induced thermogenesis* and added to the total, see Figure 4.2.

[1] A subscripted variable can take on multiple values. This is useful because it allows different types within that variable to be distinguished.

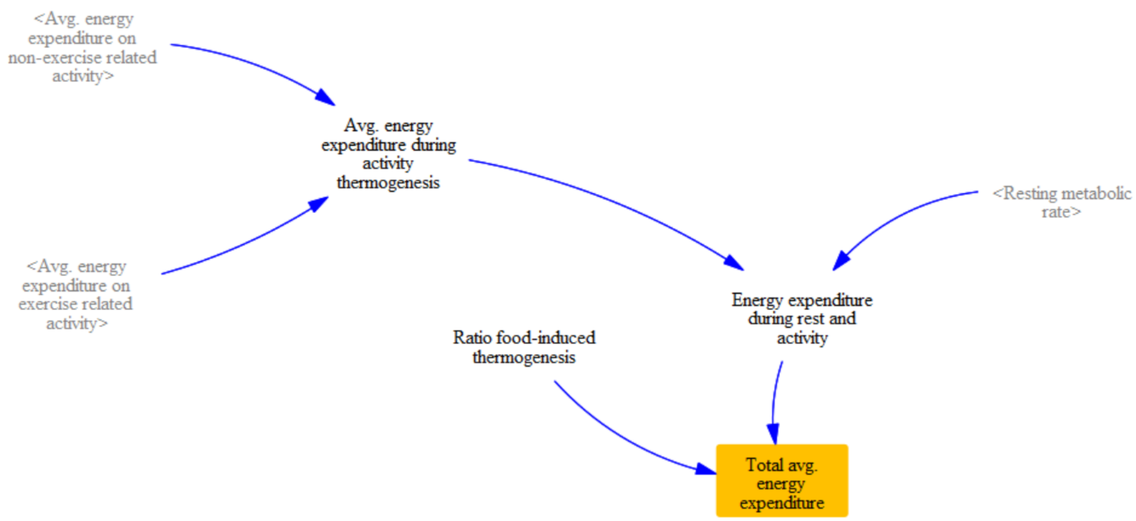

Figure 4.2 Components of energy expenditure

Each of the three components of energy expenditure is affected by socio-economic, cultural, environmental and lifestyle-related factors that determine the expense. So, each of these components is influenced by a variety of variables and can be further subdivided. The underlying mechanisms of the three aforementioned components will be discussed in the next sections.

1) Resting metabolic rate

Most of our energy is consumed with the resting metabolic rate and occurs during rest. It supports the processes of respiration, blood circulation, organ function and basic neurological processes (Mifflin et al., 1990). According to scientists this percentage ranges from around 60 to 80 percent of the total energy expended (Garrel et al., 1996; Snitker et al., 2001). Metabolism during rest is related to body composition, with increasing weight resting metabolism will also increase (Lennarz & Lane, 2013). The terms basal metabolic rate (BMR) and rest metabolic rate (RMR) both refer to energy consumed during rest and are often used interchangeably. A person's BMR is usually calculated in the morning when no exercise is performed in the last 24 hours and one is free of stress (Henry, 2005). In contrast, RMR is calculated when a person is awake and has not exercised in the last 12 hours (Bray et al., 2004). RMR is considered a better predictor for calculating energy expenditure at rest (Comphe et al., 2006), therefore RMR was chosen as the component for metabolic during rest in the current model.

To calculate RMR, the Harris and Benedict (1919) formula is widely used (Livingstone & Kohlstadt, 2005). Harris and Benedict, using statistical concepts in the 20th century, arrived at a formula that is considered a good predictor (Henry, 2005). The formula is based on weight, height and age and can be represented as follows;

$$Males\ h = 66.4730 + 13.7516\,W + 5.0033\,S - 6.7750\,A \qquad (1)$$
$$Females\ h = 665.0955 + 9.54634\,W + 1.8496\,S - 4.6756\,A \qquad (2)$$

$$where, h = kcal/day;\ W = weight\ in\ kilograms;\ S = stature\ in\ centimeters;\ A = age\ in\ years$$

However, there was also criticism due to the overestimation that occurred in some cases, especially among young women (Daly et al., 1985). Yet the formula is still used today by many scientists for making predictions on resting energy expenditure (Bendavid, 2021). Therefore, The Harris-Benedict equation is used in this model to calculate RMR. Considering population averages are modeled in the current study, the effect of overestimation of the basal metabolic rate in young women will not have a major impact overall.

The formulas of men and women were combined in this study, by taking the average of the parameter values in the equations, to arrive at a formula of the population mean. According to the CBS (2019), the self-reported height of adult Dutch people has been fairly constant since 2010. Therefore, a constant of this model, which is the average of the reported height of men and women (stature in centimeters, S), was assumed in this model. Despite the expectation of a slight increase in life expectancy in the coming years among Dutch people (RIVM, n.d), it was also assumed that the average age in the population will be constant in the coming years. The only variable factor that thus remains in the formula concerns the average weight, which is calculated in the model. The combined formula looks as follows:

$$Person\ h \quad = 682.1 + 11.7 * W \tag{3}$$

The elements of this formula in the model are displayed in Figure 4.3.

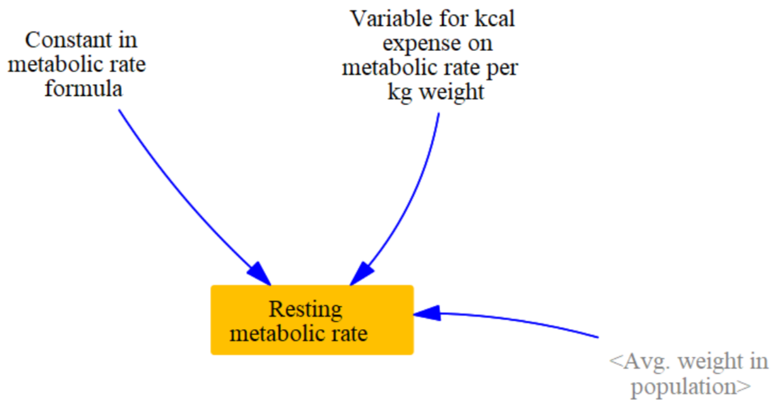

Figure 4.3 Sub model of the resting metabolic rate on neighborhood level

2) Food-induced thermogenesis

The thermic effect of consumed food covers the energy required by the body to digest, absorb and store food (Levine, 2002). There are studies that show that increased protein intake can increase energy consumption during food-induced thermogenesis (Robinson et al., 1990; LeBlanc et al, 1991). However, a critical review that assessed many studies on this phenomenon indicates that long-term studies are needed on the role of this issue on weight loss (Halton & Hu, 2004). Therefore, it was assumed in the current study that protein intake does not affect the thermic effect of food in the model.

The proportion of thermic effect of food differs between individuals but scientists indicate that this between-individual difference is negligible on the total energy expenditure (Donahoo et al., 2004). Numerous studies refer to a percentage of 10% food-induced thermogenesis of total expenditure (Hill et al., 2012; Welle, 1984; Bell et al., 2006). Based on this information, a fixed value of 10% was assumed for the *food-induced thermogenesis*. This percentage is added to the number of kcal burned during rest and activity so that total energy consumption can be calculated, see Figure 4.2.

3) Activity thermogenesis

Energy expended during activity is divided into a) exercise related activity thermogenesis and b) non-exercise related activity thermogenesis (Von Loezelhoff, 2018). Active energy consumption varies from individual to individual due to the influence of weight on movement (Levine, 2002). Weight affects two aspects of physical activity. On the one hand it influences the level of activity, in general it can be said that as weight increases, the degree of activity decreases (Johansson, 2008). This is because it is more difficult for people to make such an effort, this is directly related to the other point. People with a heavier weight burn more calories compared to people with a healthy weight (Fonseca et al, 2018; Wells & Siervo, 2011). The cardiorespiratory work in people with heavier weight seems to be higher compared to people with a healthy weight, therefore they have higher rates of energy expenditure (Leibel et al., 1995). Appendix C.2 provides a detailed overview of all the parameters in the sub-components described below.

a) Exercising energy expenditure

Exercise-related activities include all sport-related activities. To identify the expenditure during these activities, the model could be set up in several ways. For example, examining the average activity per sport plus associated consumption of that sport would provide a very detailed impression of consumption during active thermogenesis. However, data on such variables has not been found. In addition, for this model there is no need to go into detail for specific sports and associated consumption because only insight into average values are important. Another way to map this kind of expenditure is to distinguish between different places where one can exercise, such as in the gym or outside and look at the average consumption per category. However, it appears that little data has been captured in this way. Whereas data regarding the average sport activity of people in the Netherlands is known (De Hollander et al., 2022).

Biking is a widely used means of transportation in the Netherlands. Dutch researchers conducted research on the extent of walking and cycling by people of different ethnic backgrounds (Gao et al., 2017). Furthermore, the degree of social cohesion also influences people's physical activity (Mackenbach, 2016; Wang et al., 2022), since people are more inclined to meet each other outdoors and thereby perform low physical activity like walking (Kaczynski, & Glover, 2012; Mackenbach, 2016). This low intensity form of physical activity as well as walking could fall under both non-exercise related activities and exercise related activities and in this case the latter was chosen. Therefore, the amount of kcal consumed by exercise related activities is a sum of the three components of i) expenditure during sport, ii) walking and cycling, and iii) as a result of social cohesion (see Figure 4.4). Each of these aspects are explained in the following subsections.

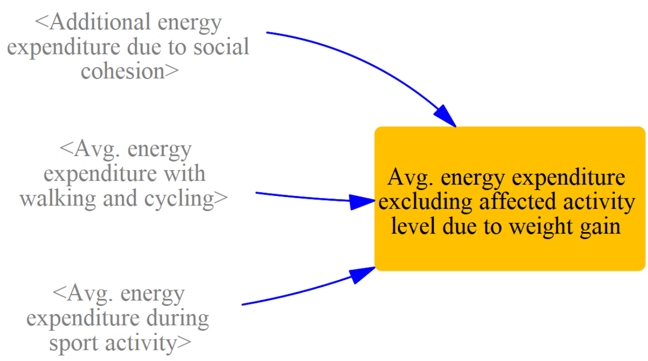

Figure 4.4 Average energy consumption excluding affected activity level due to weight gain

i) Energy expenditure due to sport activities

A variety of factors are identified as determinants of sport activity difference, causing differences in sport participation between neighborhoods. For example, income, level of education, and distance to sports facilities appear to be important (Eime et al., 2015; Kramer et al., 2015). Also, non-Western people appear to be a lot less active in Western countries compared to the Western inhabitants (Kurian, & Cardarelli, 2007). Similarly, in the Netherlands there appears to be a large difference in the exercise behavior of ethnic groups (Van Den Dool & Thiessen-Raaphorst, 2013). Therefore, in this model, ethnicity was chosen as the determining factor in calculating sport activity. Researchers Cornelisse-Vermaat & Van Den Brink (2007) conducted research on the sports participation of people of different ethnicities in the Netherlands. The results of this study have been used as input data in the model for the parameter of *avg. hours per week of sport activities*. In addition, an average value was assumed for the metabolic equivalent of task (MET) during sport activities. The MET is a unit of measurement used in physiology to express how much energy a particular activity requires. From the MET value, the oxygen consumption is calculated. Next, the energy consumption is computed using the oxygen consumption, the average weight, and a constant in the formula (Voedingscentrum, n.d.). As a final step, the time spent on sport activities and the energy consumption per minute of those activities can be combined to calculate the *average energy expenditure during sport activity*, of which Figure 4.5 shows a representation of the sub model in Vensim.

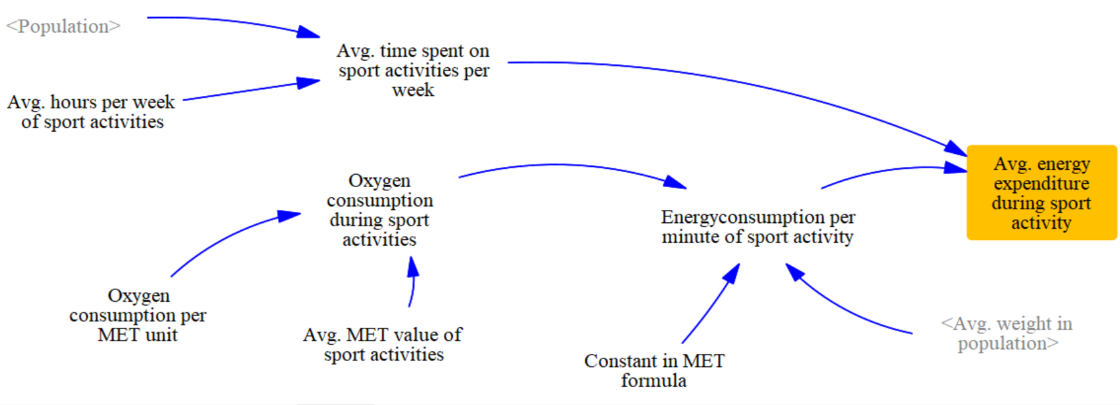

Figure 4.5 Sub model of sport activities

ii) Energy expenditure due to biking and walking

In addition to doing sports-related activities, people are also active in biking or walking for both transportation and for recreation. The Netherlands is known as the country in the world where people cycle the most. Native Dutch people are familiar with this form of transport and generally feel safe on a bicycle. For the Dutch of foreign heritage, the threshold for cycling is higher because this is often not part of their culture. Research measured how many minutes indigenous and foreign population groups spend on average per week cycling and walking (Gao et al., 2017).

The population numbers are input for calculating the average walking, cycling and sports activity in the neighborhood. The subscripted variable walking time gives the average weekly walking time for each of the ethnic groups. Based on the population groups and the average walking time for each group, the average walking time for the neighborhood can be calculated. The same process applies to calculating the average cycling time. The average expenditure during walking is 0.07 kcal per minute (Langford et al., 2017). By multiplying the latter variable by the average walking time, the average energy expenditure during walking can be determined. Similarly, the average expenditure for cycling is calculated. Figure 4.6 provides an overview of the implementation of the mechanisms of cycling and walking.

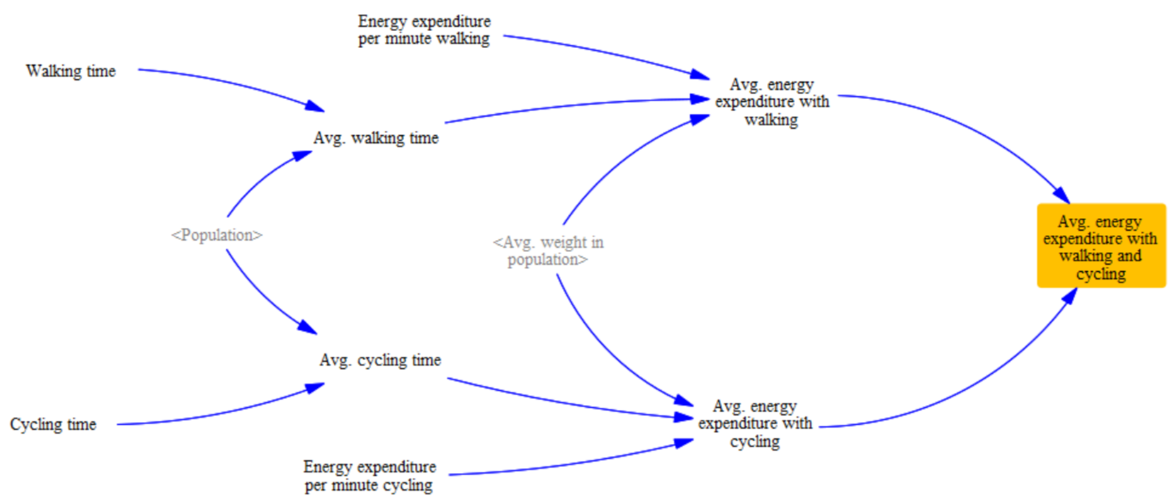

Figure 4.6 Sub model of walking and cycling

iii) Energy expenditure affected by social cohesion

Furthermore, social cohesion in a neighborhood is related to time people spend outside. This is associated with low-intensity physical activity (Mackenbach, 2016). It is suggested due to more social cohesion in the neighborhood, local residents will be more inclined to take a walk through their neighborhood, for example (Verdonk & Van Koperen, 2007). The average social cohesion by people in The Hague is assessed with a score of 5.5 out of 10 on average for the past few years (Gemeente Den Haag, n.d.). This score is determined on the basis of various aspects related to social cohesion, such as the degree of contact with other neighborhood residents, to what extent people feel at home with the people in the neighborhood and the sociability of the neighborhood. It is assumed that the average score of social cohesion in The Hague is equivalent to the average score for social cohesion so that in case of this value there will be no difference in physical activity due to social cohesion. According to Mackenbach (2016), in Dutch neighborhoods, an increase of one unit of network size in a person in the neighborhood (which is one of the measures of social cohesion) involves an increase of 2.7 minutes of physical activity per day. This value seems quite high but gives an indication. In this study, it is assumed that a unit increase in the social cohesion score of a neighborhood is equivalent to the network size of residents in that neighborhood. It was decided to set up a Lookup function[2] for this variable because it is assumed that a large difference between the measurement of social cohesion in a neighborhood and the reference point (the average measurement of social cohesion of the city of the Hague) will no longer have any effect on the level of physical activity at a given moment. In this way, a translation can be made to change in physical activity as a result of the social cohesion score in the Schildersbuurt (see Figure 4.7).

For example, in case of a small positive difference of 0.5 (out of 10) between the value for social cohesion in the neighborhood and that of the reference value, the Lookup function registers additional physical activity. On logical grounds, it is assumed that social cohesion can affect physical activity to a limited extent. Therefore, a value of 3 was chosen as the maximum and a difference between the two exceeding the value of 3 will no longer result in more or less physical activity (dependent on the sign of the difference).

[2] A Lookup function is a list of numbers that gives meaning to the x axis and y axis for specifying an arbitrary nonlinear relationship.

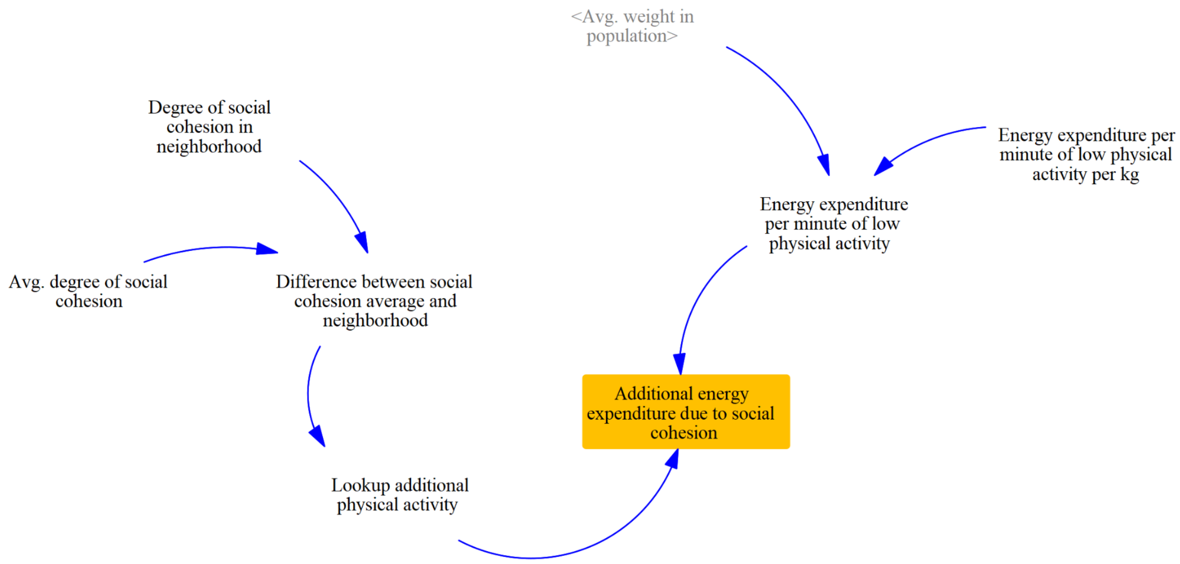

Figure 4.7 Submodel of the social cohesion

As described earlier, weight influences the level of physical activity and metabolism. Since *avg. weight in the neighborhood* affects the metabolism parameter and given that the components *additional energy expenditure due to social cohesion, avg. energy expenditure with walking and cycling* and *avg. energy expenditure during sport activity* all have *avg. weight in the neighborhood* as an input variable, the increasing metabolic aspect in case of weight gain is automatically generated within the calculations. The direct relationship of the reduction of physical activity with i) energy expenditure due to sport activities, ii) energy expenditure due to biking and walking, and iii) energy expenditure affected by social cohesion was not found in the literature. It was feasible to calculate the total decrease in exercise-related physical activity expenditure using several studies (Davis et al., 2006; Johannsen et al., 2008). Figure 4.8 shows how this has been implemented in the model and the variables related to this component are described in the next paragraph. Subsequently, this reduction is subtracted from the total expenditure of physical activity related to exercise as shown in Figure 4.9.

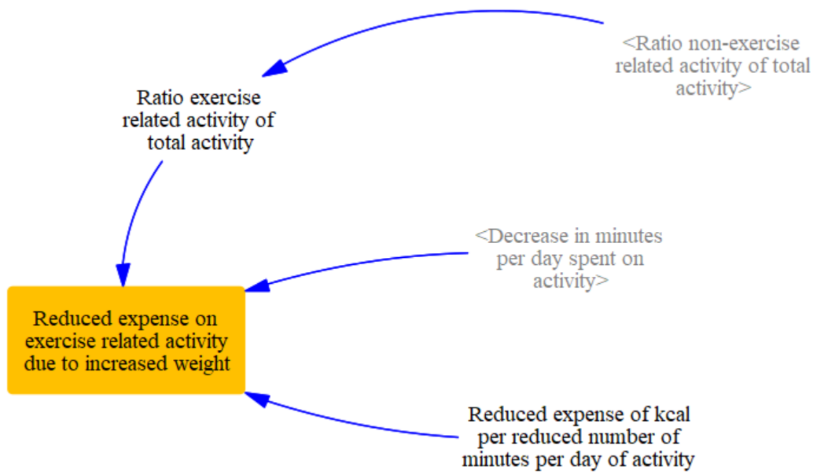

Figure 4.8 Decrease expense on exercise related activity due to increased weight

Part of the total time spent on activity is exercise related, therefore the variable for the decrease in minutes spent on activity is multiplied by the variable of the *ratio exercise related activity of total* *activity* so that the decrease in minutes spent on exercise related activity is obtained. The reduced consumption in kcal per minute of activity spent less was calculated based on a study by Johansson et al. (2008). In this study, lean individuals and obese individuals were examined for levels of activity and kcal consumption in activity, among other factors. From this, the *reduced expense in kcal per decreased amount of minutes per day spent on activity* was derived. The derivation of the *decrease in minutes per day spent on activity* due to weight gain is explained in the next section (non-exercising energy expenditure).

The *average energy expenditure on exercise related activity* thus represents the number of kcal used during planned exercising activities minus the reduction in kcal consumption due to weight gain. This is represented in Figure 4.9.

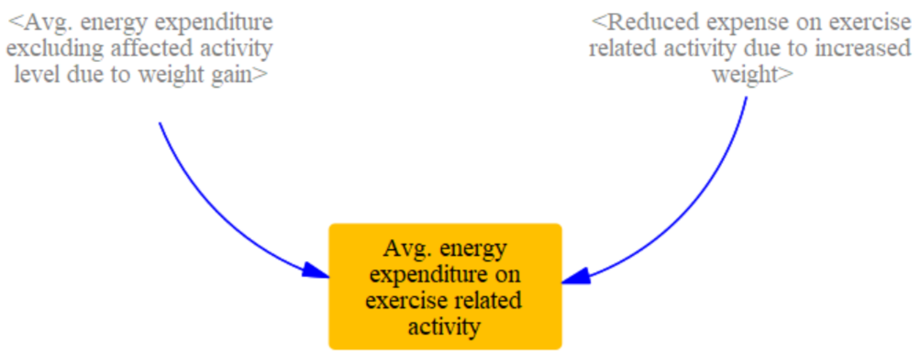

Figure 4.9. Avg. energy expenditure on exercise related activities

b) Non-exercising energy expenditure

The proportion of the non-exercising energy expenditure on the activity thermogenesis is highly variable (Levine, 2002; Chung et al., 2018). In particular, the difference lies in variations in people's lifestyles. Since non-exercise related activities involve such a wide variety of activities, it is almost impossible to ascertain the average expenditure for each of these. In addition, not much is published about the absolute value of the average amount of non-exercise related activities. Studies usually refer to a certain proportion of non-exercising activities of total activity, which according to Villablanca et al. (2015) is about 70% of the total activity. Therefore, first, the initial value for minutes per day spent on total activity per day by a person in the neighborhood was calculated. An extensive description of the calculation of this parameter can be found in appendix C. Next, this initial value is multiplied by the *ratio non-exercise related activity of total activity* to obtain the *initial value for minutes spent on non-exercising activity per day by a person in the neighborhood.*

As mentioned earlier, weight gain means a decrease in minutes spent on activity so the initial value is not sufficient for a simulation over time. Johansson (2008) conducted research on the difference in the number of minutes that healthy weight versus overweight people spent on activity. From this, the decrease in the number of minutes of activity as a result of 1 kg weight gain was calculated. It was assumed that a BMI of 23 kg/m^2 reflects a person of healthy weight. This value has been chosen since this was also the case in the referenced study by Johansson (2008). Someone with a BMI of 28 kg/m^2 reflects an overweight person. Subsequently, based on the daily weight gain, the decrease in the number of minutes spent in activity can be traced as shown in Figure 4.10.

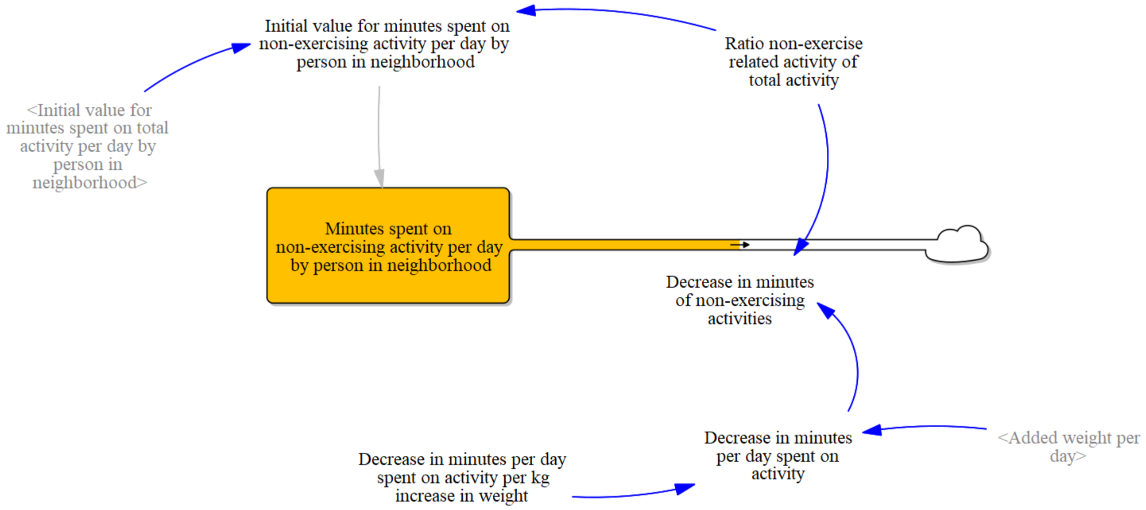

Figure 4.10 Time spent on non-exercising activity

Then the energy consumption during this part was determined by multiplying the number of minutes by the energy consumption per minute and the average weight. The energy consumed during this thermogenesis was then determined by multiplying the number of minutes by the energy consumption per minute. Multiplying by the average weight in the population directly captures the role of increasing metabolism due to weight gain (see Figure 4.11).

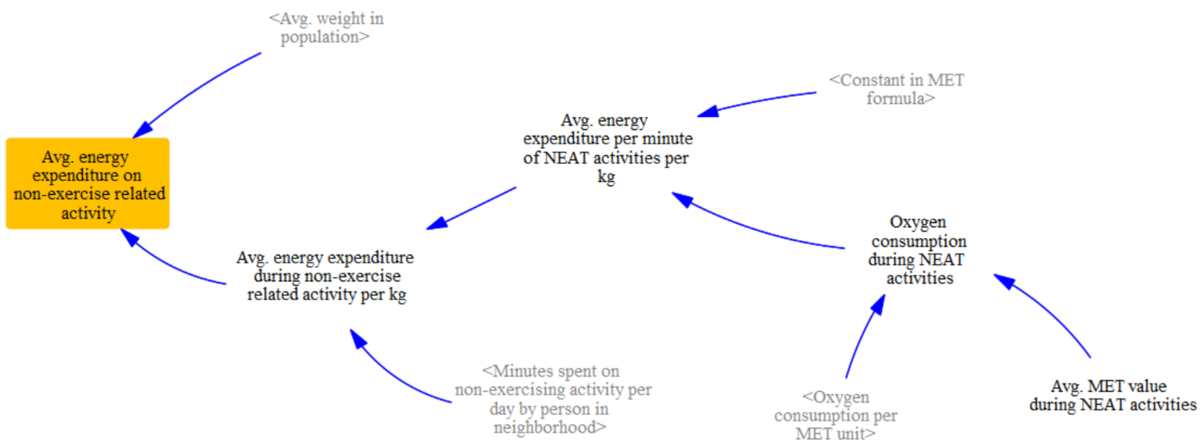

Figure 4.11 Avg. energy expenditure on non-exercising related activity

4.1.3 Energy intake

Energy is obtained from all kinds of food and drinks that we ingest in our diet. A distinction can be made between the cognitive intake and the intake that has arisen as a result of our physiology. This section discusses cognitive intake, the next section (4.1.4) deals with the physiological aspect. For the purposes of this model, there are three aspects distinguished in the cognitive determined part (see Figure 4.12). These aspects concern 1) kcal intake from food and non-alcoholic drinks, 2) kcal intake due to alcohol consumption and 3) kcal consumed due to ultra-processed diet. The reason for separating cognitively determined intake into these three aspects arises from the difference in the underlying determinants, such as ethnicity and socioeconomic status, of each aspect.

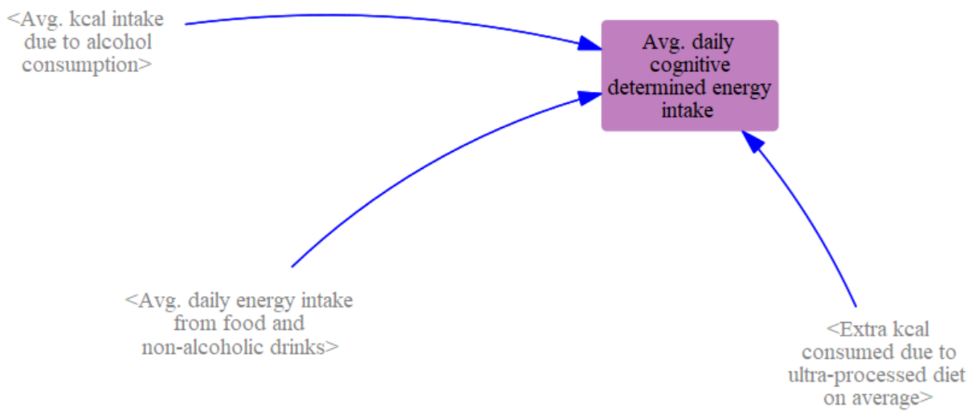

Figure 4.12 Avg. daily cognitive determined energy intake

1) Kcal intake from food and non-alcoholic drinks

The Dutch guideline for energy intake per day is 2250 kcal (Voedingscentrum, n.d.). The level of calorie intake in a particular neighborhood depends on a variety of determinants, the most important ones will be discussed in more detail.

First of all, income plays a role in food choice as income determines purchasing power. Research by Steenhuis, Waterlander, and de Mul (2011) shows that price is a determining factor in the choice of food and certainly for people with a low income. Analysis of a Dutch dataset shows that ultra-processed food is cheaper than minimally processed or unprocessed food (Vellinga et al., 2022). Low-income people therefore tend to consume more of these types of foods compared to people from a high socio-economic class. Ultra-processed foods are more unhealthy because of their high energy value and high levels of saturated fatty acids, salt and sugar (Vellinga et al., 2022). Overweight and obesity is therefore seen by some researchers primarily as an income problem (Drewnowski, & Darmon, 2005).

Another factor that determines the difference of dietary intake between groups concerns nutritional knowledge. An unhealthy lifestyle is more common among less educated people (Mackenbach, 2016). To know which foods contain the right nutritional value that the body needs, requires knowledge. The higher educated people have more knowledge about the nutritional value of food than the lower educated people. The higher educated consume a healthier diet with more vegetables and fruit (Andre et al., 2018).

Within the TNO-Project PON Overweight Network Approach researchers from TNO created the CLD in collaboration with experts and social and healthcare professionals from many different social and health domains (T. Sluijs, personal communication, December 16, 2021). Mental factors such as financial stress, depression and sleep quality were included in the CLD because they influence the intake of nutrition. Mölenberg also indicates that people with financial concerns are more likely to focus on short-term goals rather than long-term goals, such as preventing diabetes (F. Mölenberg, NPO radio 1, 2021). In order to find out the exact impact of these mental issues on kcal intake, data analyses were carried out (T. Van den Broek, personal communication, May 6, 2022) with data from Lifelines biobank (https://www.lifelines.nl), a database which contains health data from a large group of people in the north of the Netherlands and can be used to investigate health issues. The data is not freely available and for doing calculations a request by TNO was submitted earlier. The data of the factors mentioned in the Individual Overweight CLD developed by TNO (sleep quality, financial stress and depression) and kcal intake were requested from Lifelines. A data analyst at TNO, then examined the data to see if there was a correlation between the three mental related factors (sleep quality, financial stress and depression) and kcal intake (T. Van den Broek, personal communication, May 6, 2022). The results of correlation analyses showed rho values[3] (2) near zero for sleep quality and depression, which are too small to be relevant for the model. Financial stress had a rho value of -0.29 and was therefore considered a relevant factor to include in the model (Van den Broek, Personal communication, May 6, 2022). Hence, only financial stress is visible in the SD model.

Overweight is more prevalent among ethnic groups compared to native residents (Barcenas et al, 2007, McDonald & Kennedy, 2005). Possibly a difference in food intake plays a role in this. A Dutch study by De Boer et al. (2015) among Amsterdam residents of different backgrounds shows that there is indeed a difference in diets. For example, people with a Turkish origin generally eat more fruit. However, it remains unclear whether the differences in eating behavior affect their health. It is also stated that the differences may be the result of differences in education levels. In addition, Burg & Visscher (2004) argue that ethnicity is not a direct predictor of the development of weight gain. Therefore, it was decided not to include ethnicity as a predictor of food intake.

In conclusion, purchasing power, nutritional knowledge and financial stress appear to play an important role in kcal intake. These three aspects are also related to socio-economic status. Given that the relationships of purchasing power, nutritional knowledge and financial stress with food intake are difficult to ascertain, a different approach was taken. In the quantitative model these aspects are therefore implemented as constants with the value 1 added and multiplied by the intake, so that when policy options that act on these variables are experimented with they can be adjusted. The setup of this is reflected in Figure 4.13.

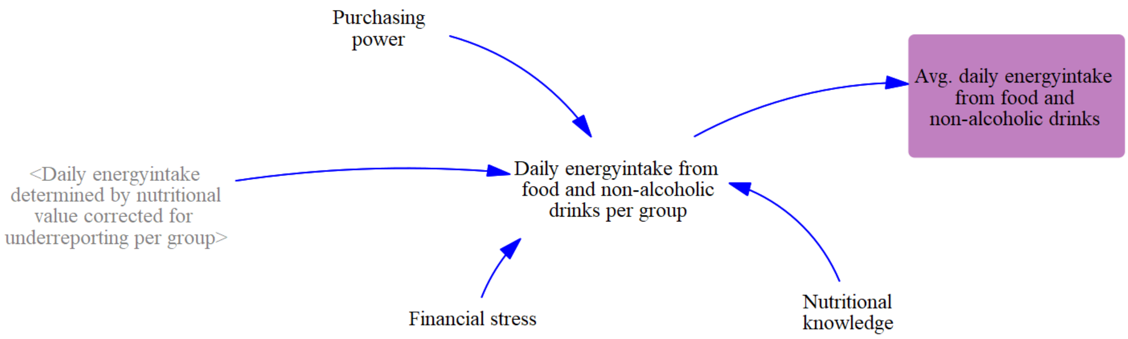

Figure 4.13. Avg. daily energyintake from food and non-alcoholic drinks

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[3] The spearman's rho test is a test performed to find out the strength of the relationship between two variables. The rho value lies between a range of -1 and 1, where -1 indicates a strong inverse relationship and 1 represents a strong proportional relationship. A value of 0 for the rho value means that no association between the two tested variables is found (Statstest, n.d.).

Between 2012 and 2016, the Dutch National Institute of Public Health conducted a population survey on food consumption (Van Rossum et al., 2020). In it, the intake of food across the population was analyzed. Food intake was mapped in several ways. For example, on the one hand the intake of foods such as potatoes, vegetables, dairy products, bread, meat, etc. was examined. On the other hand, the intake of macronutrients has been mapped. The food intake of the Dutch population could be modeled in both ways. In the current sub-model the intake of kcal is central. If the choice is made to analyze nutrients, the energy value and quantity of intake will have to be determined for each food nutrient. This is an inefficient and very time consuming process. Therefore, it was decided to model the food intake on the basis of macronutrients.

There are three large groups of macronutrients that can be distinguished; proteins, fats, and carbohydrates. In addition, there is a smaller group of macro-nutrient known as fiber (Qualls-Creekmore et al., 2020). The macronutrients contain an energetic contribution and the energetic value of macronutrient varies, each gram of protein, fat, carbohydrate, and fiber provides 4, 9, 4, and 2 kcal respectively (Jansen-van der Vliet et al., 2021).

The model distinguishes the intake of macronutrients between three levels of education, low, medium and high, using subscripts. By utilizing the average intakes of these macronutrients per level of education group, the total intake per group was derived (see Figure 4.14). The food consumption survey running from 2017 to 2021 has not yet been published. Hence, it has been assumed that the values for the intake of protein, fat, carbohydrate and fiber remain the same over time as described for 2012-2016 (Van Rossum et al., 2020). In addition, changes in the level of education groups over time have not been taken into account. The level of education among the population in the Schildersbuurt is rising, but this is happening all over the city of The Hague while overweight is still increasing (Gemeente Den Haag, n.d.)

Prof. J. Seidell (personal communication, May 19, 2022) indicates that there is always a degree of underreporting in food consumption surveys, as is the case with the one conducted by the National Institute for Public Health and the Environment (RIVM) (Van Rossum, 2020). The RIVM has already taken this into account in its measurements, but the intake shown in the report remains on the lower side. Therefore, it was decided to add another factor that corrects the food intake for underreporting (see Figure 4.14).

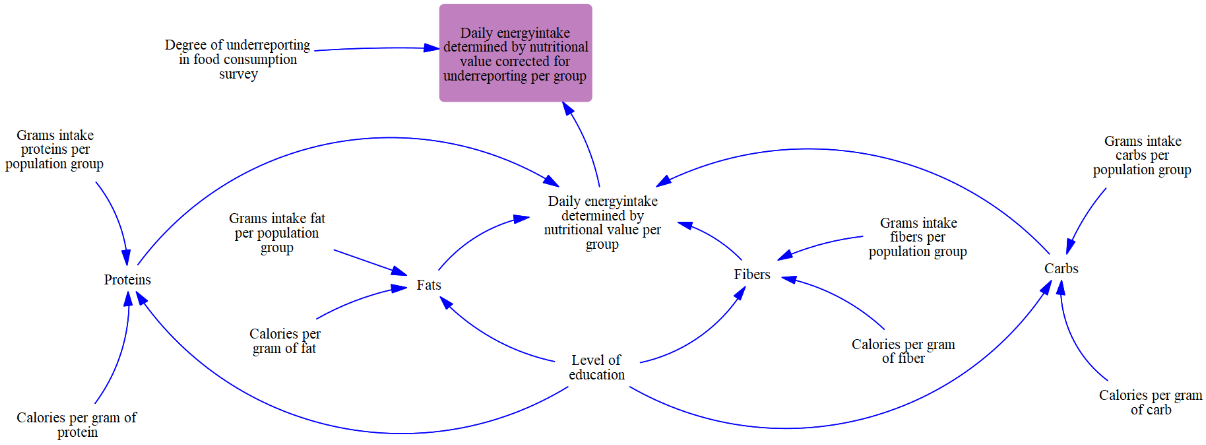

Figure 4.14 Daily energy intake determined by nutritional value corrected for underreporting per group

2) Kcal intake due to alcohol consumption

An analysis on health aspects was performed on disadvantaged neighborhoods in The Hague, neighborhoods that score significantly worse on aspects such as quality of the living environment and health and well-being of citizens, based on a survey of 2012 (Karamali et al., 2014). The report focused, among other things, on alcohol use in these neighborhoods, of which the Schildersbuurt is one. The data from this analysis serves as input data for the alcohol consumption sub-model. A distinction was made between various groups of people; non drinkers, occasional drinkers, excessive drinkers, heavy drinkers and problematic drinkers. The same classification of groups is used in the present model. In the model this is represented in the stock *distribution of population over alcohol consumption groups* (see figure 4.15).

Alcohol consumption is likely to change over time as it is sensitive to certain neighborhood-related factors. As scientists mention various factors that could influence alcohol consumption. These include aspects such as age, gender, level of education and ethnicity (Wilsnack et al., 2009; Katikreddi, 2017; Trimbos, 2020). Within this study no distinction is made between average age or gender in neighborhoods. With regards to education level, some researchers state that alcohol consumption in the Netherlands is higher among people with a high Socioeconomic status (SES) (Nagelhout et al., 2018), while Mackenbach (2016) indicates that no difference is found between people with a low and a high SES. The RIVM food consumption survey of 2014 shows that there is almost no difference between drinking behavior of people of different education levels (Van Rossum et al., 2014). The influence of educational level on drinking behavior is therefore not included in the current model.

Concerning differences in drinking behavior between ethnic groups, however, a consistent difference is found. Research suggests that ethnic minority groups drink significantly less than people of Dutch origin (Brussard et al., 2001). An analysis by the Trimbos institute shows that people with a migrant background are both less likely to be alcohol drinkers and less likely to drink heavily or problematically (Trimbos institute, 2022).

Additionally, in recent years there has been a trend in the Netherlands of drinking less alcohol (Trimbos institute, n.d.). This is possibly the result of the prevention agreement in which the government is committed to improving the health of the Dutch citizens (Ministry of Health, Welfare and Sport, 2018).

The percentage of people who do not or barely drink increased in the years between 2015 and 2020, since then it has been stable. The proportion of excessive drinkers has decreased and heavy drinking has remained stable (Trimbos institute, n.d.). This effect is represented in the model by the flow *difference due to drinking less*, which represents the change in the number of people per alcohol group per day.

The changes in alcohol consumption due to a changed composition is given by the three flows; *difference due to people entering the neighborhood (western)*, *difference due to people entering the neighborhood (non western)* and *difference due to people leaving the neighborhood*. All of which also express the change in the number of people per alcohol group per day. In the flows of people entering the neighborhood a distinction is made between western and non-western because it has been established that there is a difference in their drinking behavior. In the case of people leaving the neighborhood, it is assumed that these are people who have been living in the neighborhood for some time and therefore relate to the initial distribution of people across the alcohol groups. The calculations for the auxiliary variables for calculating the flows seen, such as initial total population and total outflow, are explained in more detail in Appendix C.3.

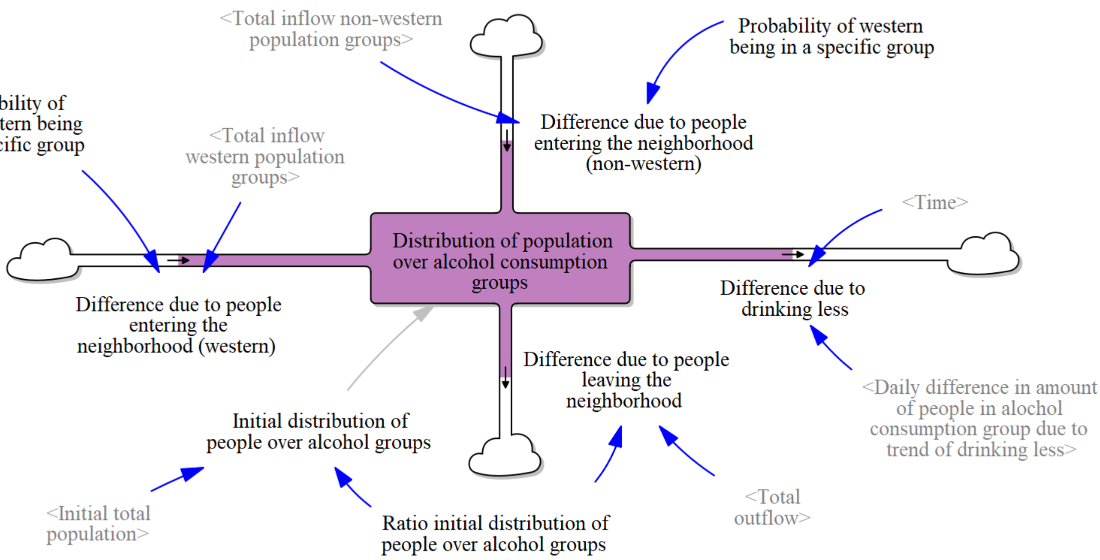

Figure 4.15. Submodel of distribution of population over alcohol consumption groups

The distribution of people over the five different types of alcohol users (non-, ocasional, excessive, heavy and problematic) provides the basis for calculating the number of average kcal alcohol consumed. The people in a particular group are multiplied by the average alcohol consumption of that group after which the total consumption is divided by the entire population (see Figure 4.16).

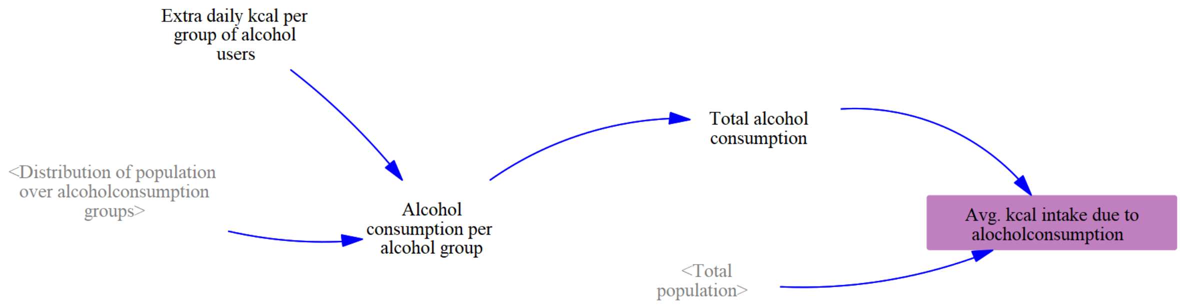

Figure 4.16. Submodel of alcohol consumption

3) Kcal consumed due to ultra-processed diet

In recent years, the influence of the supply of food on overweight has become more and more apparent. People are seduced into an unhealthy diet by what is offered to them in the environment (Mensink & Feunekes, 2015; Seidell & Halberstadt, 2015). The number of fast food chains has also grown enormously in recent years. Research firm Locatus keeps track of what kind of stores are located in a neighborhood. Pointer (KRO-NCRV) performed analyses with this data to find out the growth of the number of unhealthy suppliers in the past ten years per neighborhood in the Netherlands (Pointer (KRO-NCRV), 2021). To derive what the number of unhealthy suppliers means for the change of eating behavior, the dissertation of J.D. Mackenbach of the Vrije Universiteit in Amsterdam (2016) was consulted, in which the number of people with an ultra processed diet was determined based on the number of unhealthy suppliers per 10,000 inhabitants. Therefore, first, the *unhealthy food suppliers per 10,000 citizens* in the neighborhood was calculated. This was then converted to the number of *unhealthy suppliers per person*. And using the insights of Mackenbach (2016), a Lookup function[4] in Vensim was created for the *percentage of people having an ultra-processed diet* as a result of the number of unhealthy selling points, The aforementioned model components are reflected in Figure 4.17.

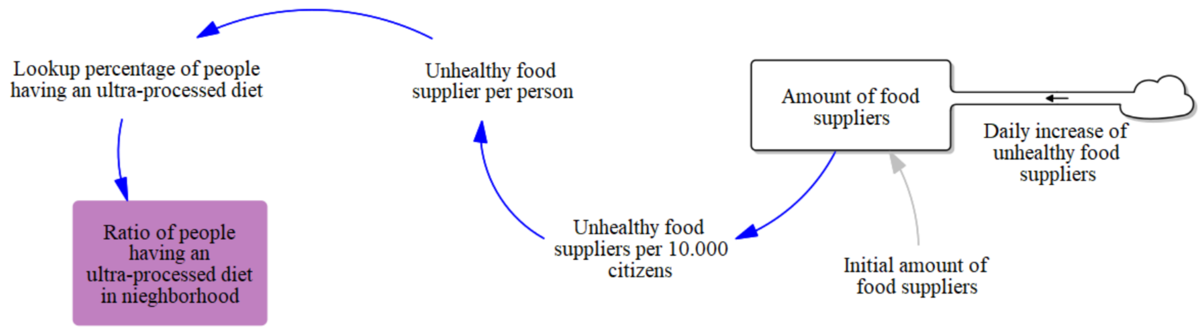

Figure 4.17 Percentage of people having an ultra-processed diet

It is assumed that there was already some degree of ultra-processed dietary behavior among the whole population at the start of the simulation. Since the data from the food consumption survey covered the entire population, the current study looked at whether the proportion of people on such a diet deviated from that of the general population. According to Hall et al. (2019), the number of extra kcal consumed per day by people on an ultra-processed diet is 500. Using the parameters for the difference

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[4] A Lookup function is a list of numbers that gives meaning to the x axis and y axis for specifying an arbitrary nonlinear relationship (Ventana Systems, 2010).

in ratio of people having an ultra-processed diet and *total population*, the total *extra kcal consumed due to ultra-processed diet* in the neighborhood is determined. By dividing this extra amount of kcal by the total population enables the *extra kcal consumed due to ultra-processed diet on average* to be calculated (see Figure 4.18).

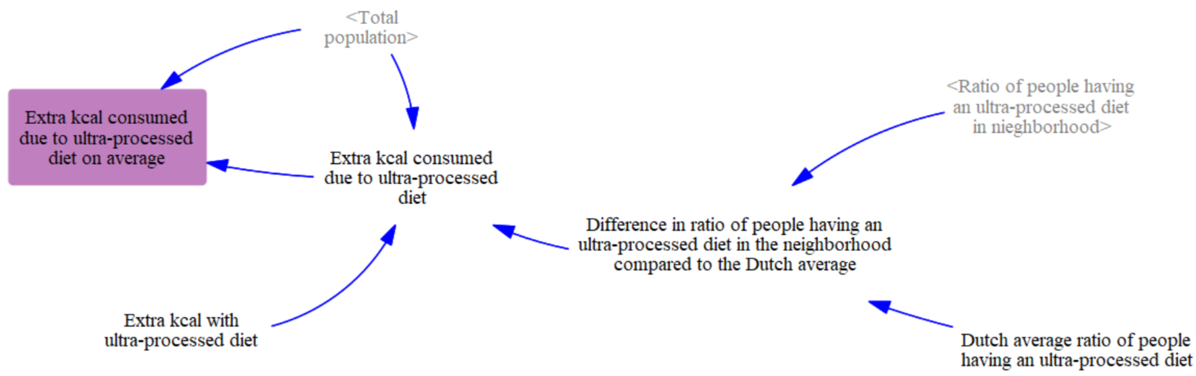


Figure 4.18. Extra kcal consumed due to ultra-processed diet

4.1.4 Effect of energy expenditure on food intake

In addition to the above mentioned factors of food intake, there is also an internal reaction that influences food intake. Energy expenditure encourages energy intake (Milder et al., 2011). This mechanism is important for survival (Bosy-Westphal et al., 2021). When someone expends a lot of energy, a hunger signal will be emitted in the brain that prompts them to consume more food. The same effect works the other way around, if someone uses little energy, the body will ask for less energy, which suppresses the consumption of food. The strength of this mechanism differs greatly from person to person due to differences in physiological characteristics, making it difficult to predict the response of exercise for individuals (Blundell et al., 2015). According to Westerterp-Plantenga (2001), food intake is determined 50% cognitively, the other 50% is physiologically determined. Therefore, the *ratio physiologically determined intake* in the model involves a value of 0.5. The degree of physiological intake is determined by the proportions of energy expenditure and intake. A higher or lower amount of physical activity can lead to a difference between expenditure and intake and by multiplying this by the ratio which is determined physiologically, the level of physiological intake can be estimated. The hormone leptin plays a role in this. Leptin is a hormone mainly secreted by white adipose tissue that inhibits appetite. With prolonged increased physical activity, less leptin is released which increases appetite. (Bouassida et al., 2006; Milder et al., 2011). Bouassida et al. (2006) reviewed several studies on this mechanism and concluded that a difference in the amount of leptin release occurs after 12 weeks of changed degree of physical exertion.

Studies have mainly investigated the effect of increased levels of physical exertion on appetite rather than the effect of decreased levels of physical exertion on appetite (Milder et al., 2011). According to the appetite control system, the intake of food would be suppressed with reduced exercise (Blundell et al., 2015). Therefore, in this study it is assumed that higher levels of exertion leads to an increase in appetite and lower levels of exertion leads to a decrease in appetite.

The total average intake thus amounts to the intake determined by cognitive and physiological factors, represented by the variable total avg. energy intake in Figure 4.19.

The choice to only model the effect of consumption on intake stems from a study by Hall et al. (2012) who found that increased energy intake has almost no effect on metabolism.

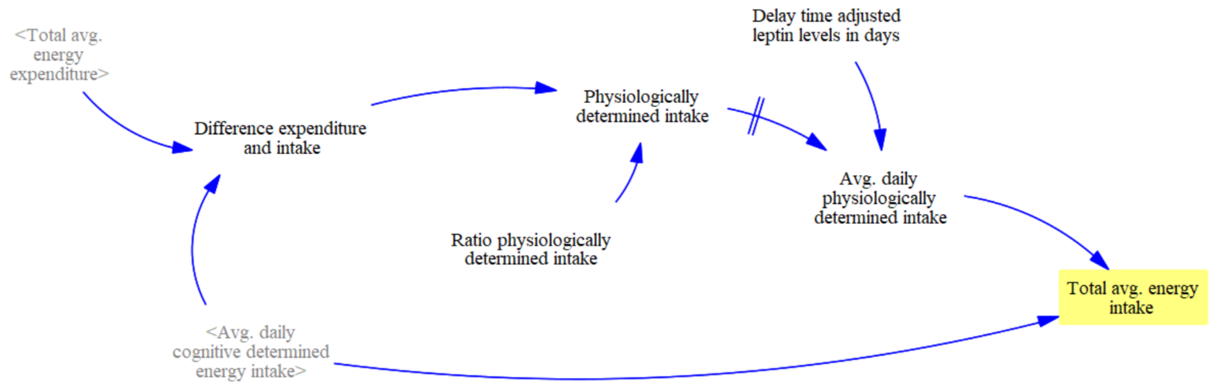


Figure 4.19 Submodel of effect of energy expenditure on food intake

4.1.5 Effect of smoking cessation on weight gain

By quitting smoking, most people experience an increase in their body weight. Some studies suggest that nicotine inhibits cravings so quitting nicotine could lead to increased kcal intake (Moffart & Owens, 1991; Stamford et al., 1986). The exact mechanism responsible for this still seems unclear (Filozof et al., 2004). A study by Rodin et al. (1987) shows that weight gain occurs after smoking cessation but that an increased intake is not the cause. In addition, studies suggest that a lowered resting metabolism occurs as a result of quitting nicotine (Dallosso & James, 1984; Moffart & Owens, 1991), while this is contradicted by other studies (Ferrara et al., 2001; Jensen et al., 1995). The influence of smoking cessation is therefore associated with weight gain and not with intake or resting metabolism in this model. In addition, the weight change varies greatly between people who quit smoking, for example, there are those in whom their weight decreases. On average, a non-smoker gains 4.5 kg in weight during the first year, after which the weight stabilizes (Audrain-McGovern & Benowitz, 2011).

People are becoming increasingly aware of the serious consequences of smoking and there are more and more people who are giving up this addictive habit. The figures of people who smoke in the Schildersbuurt of the years 2012, 2016 and 2020 are known (Gemeente Den Haag, n.d.). There is also an expectation of the smoking behavior of Dutch for the next 20 years (RIVM, n.d.). It is assumed that this trend also applies to the Schildersbuurt. Based on these figures, the number of smokers at the start of the simulation and the number of quitters over time were calculated. There are annual differences in population numbers and this also influences the number of smokers in the neighborhood as part of the increased population could also be smokers. Figure 4.20 provides an overview of the quantitative sub-model of the weight gain due to smoking cessation. Appendix C.5 elaborates on this sub-model.

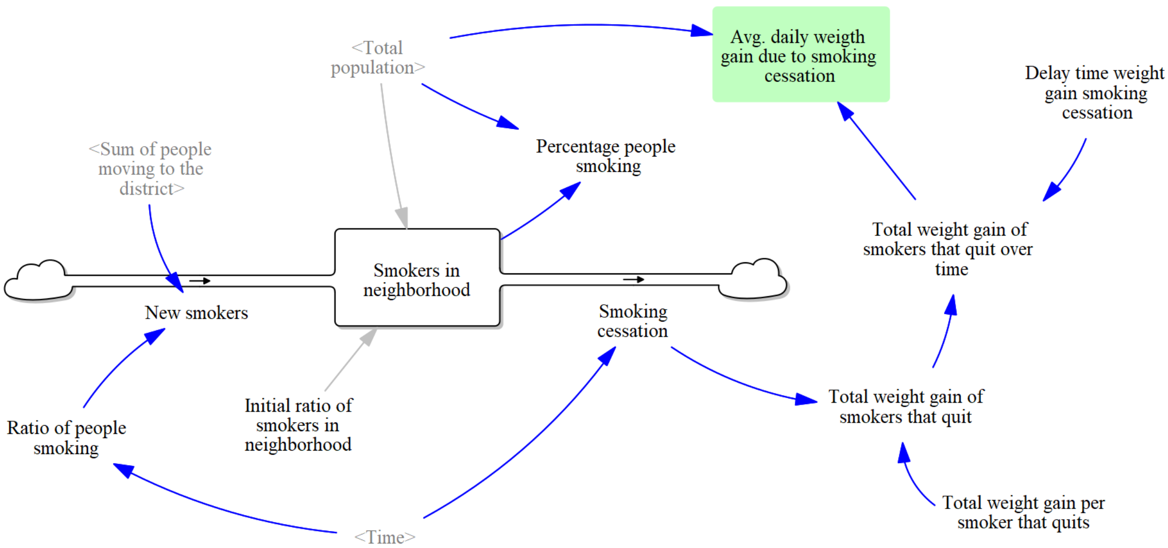


Figure 4.20. Submodel of weight gain due to smoking cessation

4.1.6 Degree of overweight in the population

First of all, energy imbalance is determined by energy expenditure and energy intake. A disturbed energy balance leads to weight gain if the calorie intake is greater than the calorie consumption. Research shows that with a difference of plus 10 kcal per day (i.e. an energy imbalance of plus 10 kcal per day) one gains about 0.5 kg in a year (Brown et al., 2005). In the model this is represented as the *annual weight gain per daily kcal energy imbalance*. The *energy imbalance* and the *daily weight gain per daily kcal energy imbalance* together form the *average daily weight gain* for people living in that neighborhood. In addition, the *average daily weight gain due to smoking cessation* discussed in the previous section is also part of this variable. The model representation of these mechanisms is shown in Figure 4.21.

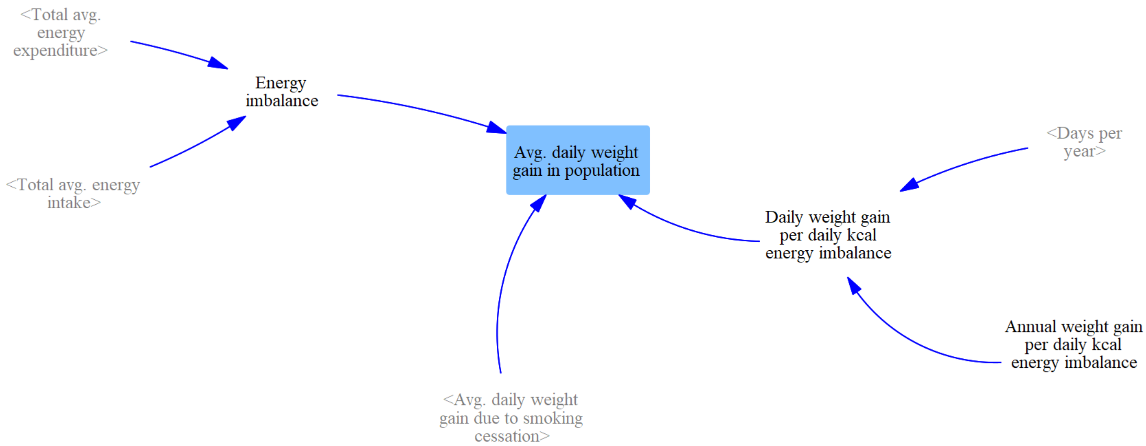


Figure 4.21 Submodel of average daily weight gain in population

It takes some time for a positive imbalance in the energy equation to convert to body fat. Half of the weight gain caused by the imbalance occurs within a year. After 2 years, 95% of the final weight gain has occurred (Hall et al., 2011). A third order exponential delay[5] was selected for the variable *added weight per day* for this reason. So that the weight increases gradually from the emergence of the energy imbalance as shown in Figure 4.22. To calculate the initial value of the average weight of people in the neighborhood, the *average weight of a healthy weight person* and the *average weight of an overweight person* was investigated, an explanation of this can be found in Appendix C.3.

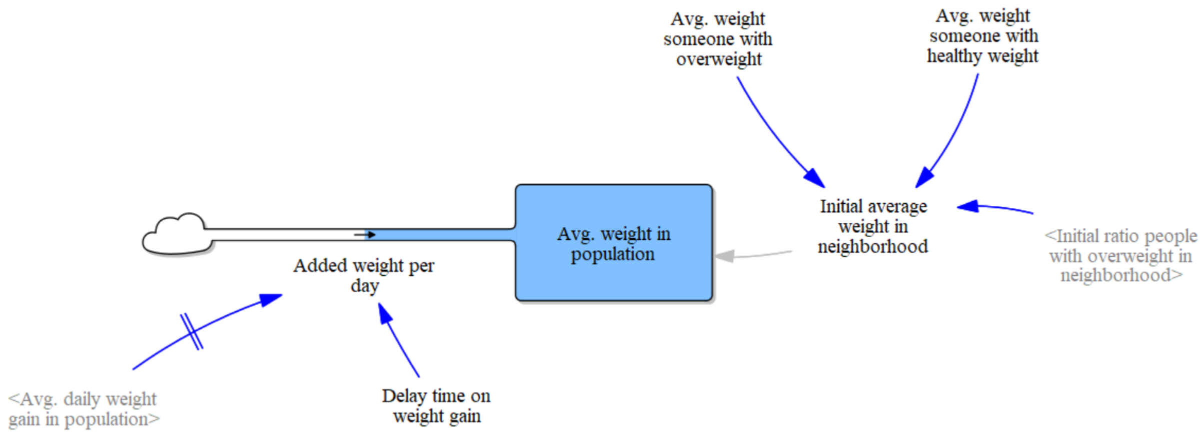


Figure 4.22. Submodel of average weight in population

The next step is to find out how the avg. *added weight per day* by people in the neighborhood relates to the ratio with which the population of overweight in the neighborhood will increase. To do so, it is important to determine the *daily ratio increase in overweight population per kg daily weight gain*. A report by Van der Bie et al. (2012) describes the difference in body weight and the difference in percentage of overweight people among the same Dutch population between 1991 and 2011. From this it can then be deduced how the average weight change affects the percentage of overweight people in the neighborhood (in the calculations, a correction was made for population growth) and thus the *annual ratio increase in overweight population per kg annual weight gain*. By multiplying this percentage by the number of people with a healthy weight in the neighborhood, the number of overweight people is eventually calculated. However, this report gives a rather low value. It was therefore decided to calculate this by means of more recent data from CBS. For this purpose, data from 2015 to 2020 was used (CBS, 2019; CBS et al., 2021). The *annual ratio increase in overweight population per kg annual weight gain* is similar to the *daily ratio increase in overweight population per kg daily weight gain* since both the ratio increase in overweight population as well as kg weight gain go from annual to daily values (See Figure 4.23).

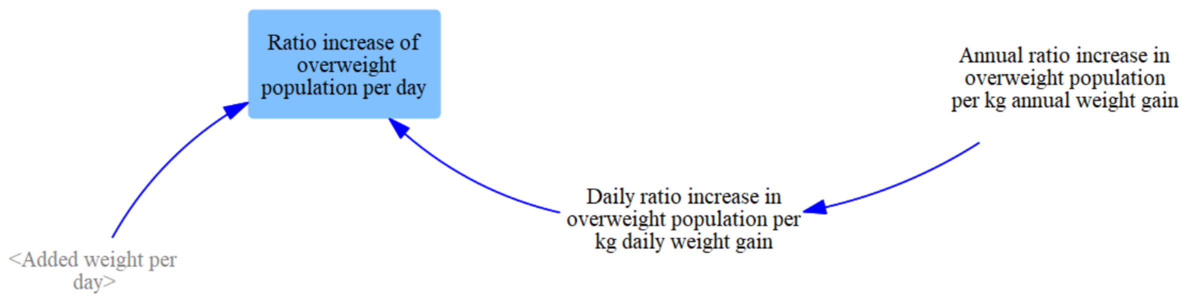


Figure 4.23 Submodel of ratio increase of overweight population per day

[5] A third order exponential delay represents a gradual course of the value of an input variable over time where the delay time is a measure of the spread of this process (Ventana Systems, 2010).

Eventually the number of overweight people in the population at a certain time point can be calculated. The initial ratio for the number of people with a healthy weight is the starting value of the stocks for people with a healthy weight and people who are overweight. This assumption is made because the weight class distribution of people moving to the neighborhood is unknown and is likely to be fairly in line with people already living in the neighborhood. The stocks are also influenced by healthy weight or overweight people moving into or out of the neighborhood which is represented by the flows on the outside. The inflows now reflected by the three flows in Figure 4.24 could also represent an outflow if the value of the parameter of that flow becomes negative. It is assumed that people moving into or out of the neighborhood have a probability of being overweight equal to the initial value of overweight people in the neighborhood. Appendix C.6 presents an explanation of the flows and variables from Figure 4.24.

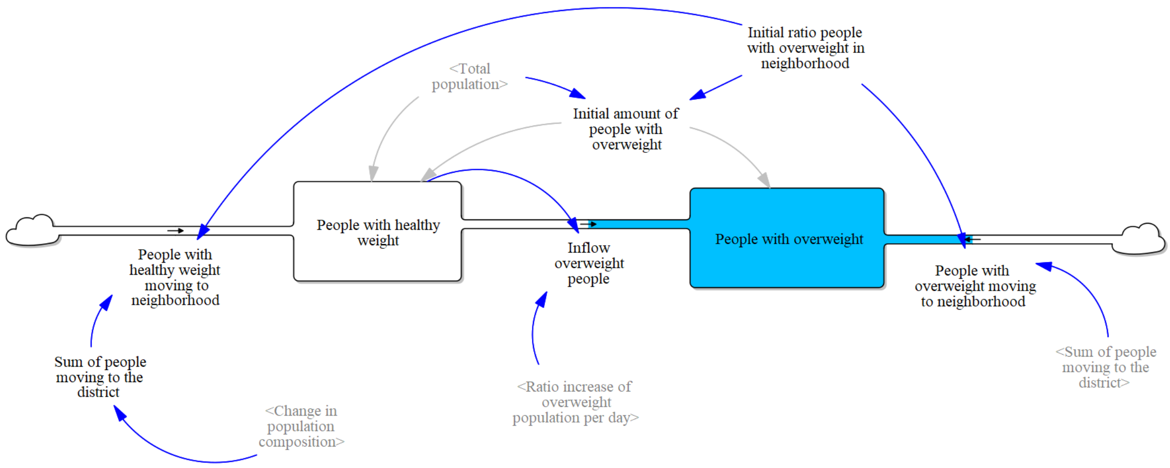


Figure 4.24. Submodel of overweight population

With the stocks in Figure 4.24, the percentage increase in overweight people relative to the initial value was calculated so that the increase in overweight people over time can be examined. This is represented in the variable Percentage people with overweight in neighborhood (see Figure 4.25).

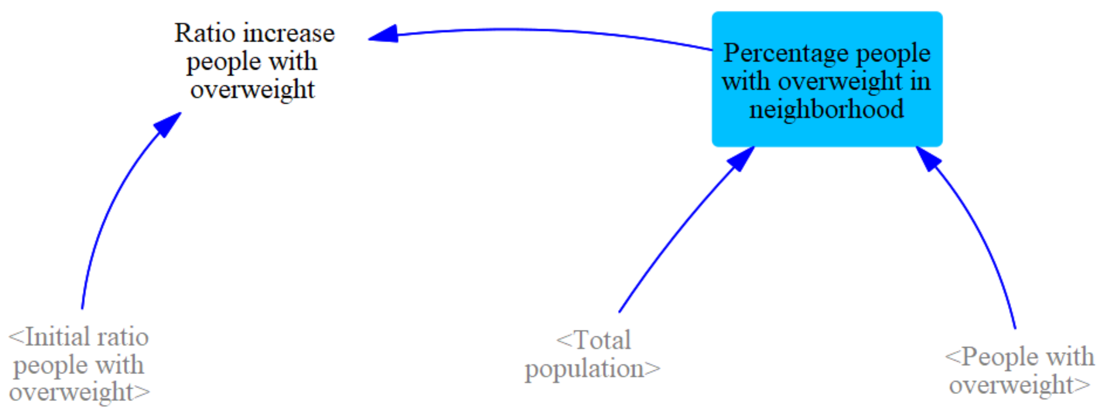


Figure 4.25. Submodel of overweight population

4.1.7 Summary of the model formalization process

The model formalization section highlights all model components that have been modeled for the purpose of the model objective. The values of and relationships between variables have been quantified and have been substantiated using the literature where possible. Missing information for which assumptions had to be made has been indicated in the section as well. In Appendix C a complete overview can be found per component representation with all the corresponding values, functions and sources.

4.2 Simulation settings and base case results

The base case simulation reflects the model behavior in the Schildersbuurt based on the implemented data and under the assumptions made. For the integration method of the simulation in Vensim the Euler method was chosen, given the presence of discrete functions, such as IF THEN ELSE functions (see e.g. variable *people moving to the neighborhood* in Table C.1), this is the best option.

One of the advantages of SD is that it is well suited for simulating long time periods (Pruyt, 2013) which allows the effects of policy options to be properly evaluated. Data obtained as input for factors in the model is derived from the years 2015 up to and including 2020. The model attempts to provide an estimate for the course of overweight from January 1, 2015 to December 31, 2025, which means that the model runs for 11 years. This allows the longer-term effects of policy interventions to be examined. Since the output of the model is given in days this number is in the model rounded to 4000 days (ca 11 years). The scale of time axis in the plots has been converted to years with the use of a script of the computer programming language Python (version 3) (Van Rossum & Drake, 2009) (see Appendix C.8).

The results of the KPIs *people with overweight* and *percentage people with overweight in neighborhood* are represented in Figure 4.26 and 4.27. Both KPIs show a gradual increase in their values over time. Noteworthy is the decrease in the growth of the values of the KPIs that starts around 2021, from this point the KPIs continue to increase but the growth is less than the years before. The base case simulation indicates that slightly more than 18200 people in the neighborhood are overweight in 2015 and this will increase to about 18700 in 2026. The percentage of overweight people in the neighborhood in the base case simulation is about 57.8 in 2015 and increases to 59.0 in 2026. The underlying drivers in the model that account for this behavior are given in Appendix C.7.

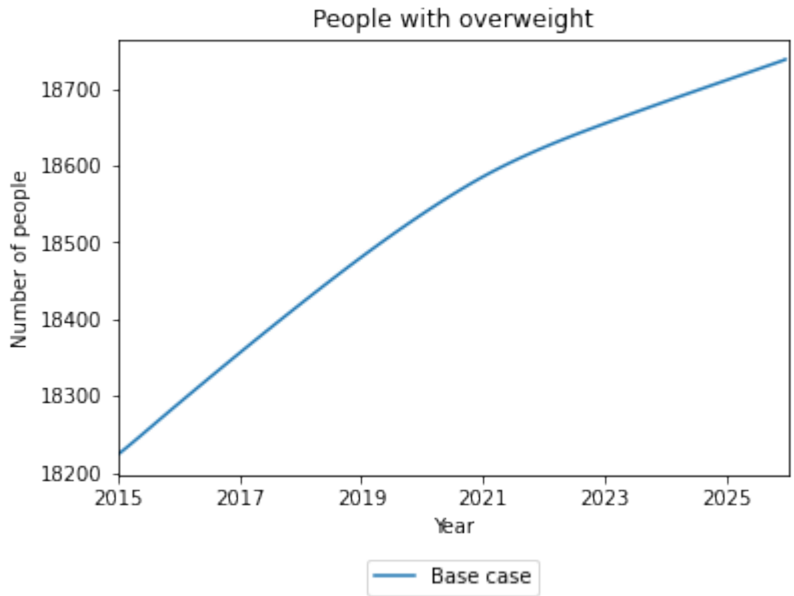


Figure 4.26. Base case result people with overweight

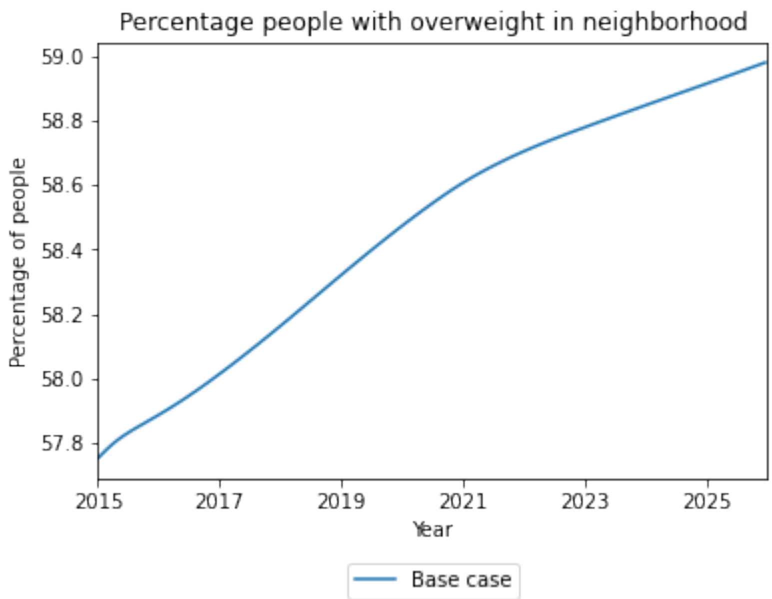


Figure 4.27. Base case result of percentage of people with overweight in neighborhood

4.3 Verification and validation of the built model

During the process of establishing the qualitative model, it was checked repeatedly that the model could still run after adding new elements. Experts with knowledge of the domain were also consulted several times to verify that the model made sense. The purpose of this section is to further increase confidence in the performance of the built model. The model will never be able to be considered verified or valid because it is constructed with simplified formulations of actual reality behavior (Sterman, 2000). However, the usefulness and shortcomings of the model can be exposed. The pioneers of system dynamics modeling have developed tests with a wide range of approaches for this purpose (Forrester & Senge; 1980). For the current Neighborhood Overweight model, both static (without simulation) and dynamic (with simulation) tests are applied. Tests for boundary adequacy, dimensional consistency, integration error, extreme conditions, sensitivity analysis, and historical validation were performed as described below.

4.3.1 Boundary Adequacy

The boundary adequacy test is applied to check whether the quantitative model is able to simulate the behavior one wants to investigate by the means of the model. The definition can be described in the following terms; "The boundary-adequacy (behavior) test considers whether or not a model includes the structure necessary to address the issues for which it is designed" (Senge & Forrester, 1980, pp. 27). Within boundary adequacy assessment the model is compared to the structure derived from the literature and the CLD by TNO. The test verifies that the important concepts and structures required to address the perceived problem are modeled endogenously (Qudrat-Ullah & Seong, 2010). For this report only a qualitative assessment of this test is performed.

The KPIs defined in the model to answer the research question concerns the number of *people with overweight* and *percentage of people with overweight in the neighborhood*. The KPIs are determined endogenously in the model using variables from various model components. Similarly, the main concepts for quantifying the KPIs, such as the *energy expenditure*, *energy intake* and *energy imbalance* (J. Seidell, personal communication, May 19, 2022) and the underlying concepts required to translate the *energy imbalance* to the KPIs such as the *average daily weight gain in the population*, *added weight per day* and *ratio increase of overweight population per day* are endogenously defined in the model.

The connections that are made between different model components such as the influence of *energy expenditure* on *energy intake* and the influence of the *energy imbalance* on *avg. daily weight gain* concern highly physiologically complex processes. The scope of this model focuses on quantifying overweight on a population level and not on a more disaggregated individual level. Hence, justifying the choice to not include a lot of physiological variables in the model, but to focus on the key physiological processes determining the state of overweight of the individual.

The model does not distinguish between the extent to which an individual has excessive weight. The effect of certain components on weight, for example that more exercise will lead to weight loss and is in the current model generalized to population level which implies that the overweight population decreases, while in reality it could also be the case that severely overweight people become slightly less overweight.

A number of studies examine the relationship of separate variables such as, for example, the relationship of age or ethnicity on walking behavior (Gao et al., 2017). When using such sources it was therefore not possible to quantify both variables as input and in this case the factor that plays the largest role in the relevant neighborhood, the Schildersbuurt in this case, was chosen.

In the model, averages are assumed for elements, such as for the MET value of sport activities and the MET value of non-exercising activities. In reality both sport activities and non-exercising activities consist of a range of activities all with their own MET value. This could be modeled more specifically, but given the fact that specification of details is not seen as one of the most important aspects of modeling (Sterman, 2000) and because the population and thus average values are central, this can be defended.

4.3.2 Dimensional Consistency

The units associated with variables in the model are described in the tables in Appendix B and correspond to dimensions from reality. To measure the internal validity of a model, Schwaninger & Groesser (2020) recommend the dimensional consistency test which verifies the equivalence of the units on each side of the equations.

Within Vensim, there is a functionality that provides for testing units for each equation in the model and communicates back what unit errors and warnings are found. After executing this functionality on the model it turned out that no unit errors occur and only warnings were found for lookup functions. The warnings for these lookup functions are not problematic since they arise from the properties of these functions. On this basis it is concluded that there exists dimensional consistency.

4.3.3 Integration Error

In order to use a mental model as a basis for advice for new policy interventions, inferences will have to be made from decisions for which no data exists. We humans would not be able to do so given the higher order nonlinear differential equations involved, given the computational challenge (Sterman, 2000). SD enables continuous simulation of those tasks using numerical integration. It is important that the integration method and time step are aligned (Pruyt, 2013).

The integration techniques available in Vensim are Euler, Diff, RK4 Auto, RK4 Fixed, RK2 Auto, RK2 Fixed. The best option for a model depends on the objective and properties of the model. The current model contains discrete functions (e.g. IF THEN ELSE functions) making only Euler integration a suitable method (Vensim, n.d.). When choosing the Euler method, it is important to select a small time step otherwise insufficient accuracy may occur (Pruyt, 2013).

Other points of interest in determining the correct time step are the ratio of the time step to the smallest time constant or delay time. In addition, the time step should also be smaller than the constant of the delay divided by 4 times the delay order. Also, it should be avoided to choose an unnecessarily small time step as it takes more time to run. In addition, a small time step has a negative influence on integration errors and round-off errors (Pruyt, 2013). To achieve an optimal time step, the time step can be halved so that integration errors can be detected (Sterman, 2000; Pruyt, 2013).

A simulation run for all possible time steps in Vensim has been examined (see Appendix D.1). Based on these results, a time step of 0.0625 days was chosen. Halving the time step to 0.03125 does not lead to significant changes in the outcomes of the model. This suggests that the model is excluded from integration errors.

4.3.4 Extreme Conditions

The model should also behave realistically under extreme conditions (Sterman, 2000). For the extreme condition test, the values of parameters are set extremely high and extremely low. This offers the possibility to provide insight into the solidity of the model (Forrester & Senge, 1980). Given time constraints not all parameters could be investigated. For the selection of the parameters, the importance of parameters in the model and their variability was taken into account. The following five parameters had been chosen to test with extreme values:

- Initial population
- Smoking cessation
- Social cohesion
- Degree of underreporting
- Ratio additional intake of the difference

Appendix D.2 describes the elaboration of the extreme values test. Most important insights provided by the extreme condition test concern;

- The model is not compatible for extremely low values of the initial population numbers (i.e. less than 6 persons per ethnic group) given the incompatibility of the lookup function *number of people with an ultra-processed diet* for extremely low values. However, such low population numbers will probably never occur in reality. And for neighborhoods with few inhabitants, the number of unhealthy food suppliers will also be smaller, resulting in a lower ratio of suppliers per person, which means that the model is still compatible in such cases.
- In the rest of the cases, the model corresponds to the stated hypothesis of the extreme values for the parameters.

4.3.5 Sensitivity Analysis

A sensitivity analysis is performed to test whether small changes in parameter values generate credible behavior in the model. At the same time possible errors can be detected. The values of some parameters are adjusted after which the behavior exhibited by the model is examined. The graphs resulting from the simulations will be assessed for comprehensibility. The value of tested parameters are adjusted by +/- 10% which is a common range for sensitivity analyses (Sterman, 2000). Thus, the adjusted variables for this test are as follows:

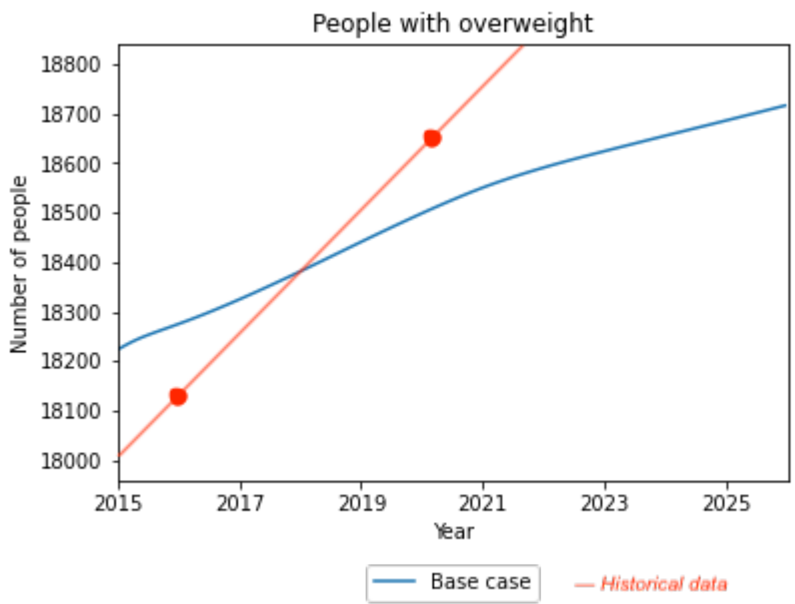
- Degree of underreporting: the extent to which people report lower food intake than their actual intake.
- Ratio physiologically determined intake: the ratio of intake determined by physiological processes in the body
- MET value during sport activity: the value of Metabolic Equivalent of Task for sport activities
- Annual increase unhealthy food suppliers: the annual increase of unhealthy food suppliers in the neighborhood
- Initial ratio people with overweight: the initial ratio of people in the neighborhood who are overweight

The results of the univariate sensitivity analysis are shown in Appendix D.3. No uncertainty was found that influenced the behavioral mode, which refers to changes in the patterns of behavior. There was only numerical sensitivity encountered indicating numerical differences in model results (Sterman, 2000). It becomes clear that small variations in the *degree of underreporting* could lead to a 0.3 percentage point difference in the percentage of overweight people by the end of 2025. This is plausible given that the *degree of underreporting* affects *avg. daily energy intake from food and non-alcoholic drinks*, which is a major determinant of *total avg. energy intake*. The sensitivity test results of the variable *ratio physiologically determined intake* show little change in the model's behavior. This can be explained by the fact that the difference between the *total avg. energy expenditure* and the *avg. daily cognitive determined energy intake* is small, a value between 2 and 3 kcal over time. The

ratio physiologically determined intake is multiplied by this difference, resulting in a small contribution of kcal intake determined by physiological factors to the *total avg. energy intake*.
A small change, of -/+10%, in the *MET value of sport activities* results in significant consequences for the behavior of the system in the current model. For instance, it leads to a difference in the number of overweight people ranging from 18450 to 18800 by the end of the simulation (i.e., end of 2025). This can be justified by the fact that this parameter is a large determinant for the energy expended during sport activities, of which the latter plays an important role in the total energy expenditure. A small number of *annual increase unhealthy food suppliers* in the neighborhood more or less shows little effect on the overall model behavior, with a maximum of 25 more or fewer overweight people by 2025 compared to the base case. This is because the kcal intake resulting from an unhealthy food environment has a relatively small share in the overall energy intake in this model. Small adjustments of -/+10% for the *initial ratio people with overweight* could result in the amount of people with overweight ranging from 17500 to 20200 by the end of the simulation. The large impact of adjustments in the *initial ratio people with overweight* is logical because this parameter is at the base for determining the starting value of the KPIs in the simulation.

4.3.6 Historical data validation

Data from the municipality of the Hague, The Hague in figures (2022), only has historical data for the years 2016 and 2020 of the percentages of people in the Schilderbuurt who are severely overweight (BMI of 30 kg/m^2 or more). Therefore, historical data on the proportion of overweight people was requested from data source OpenInfo, which appeared to have the data for this group for the years 2016 and 2020. The percentage of overweight people in 2016 amounted to 58% and in 2020 to 59%[6] (W. Van Bijsterveld, personal communication, July 7, 2022). The population in the Schildersbuurt consisted of 31,255 people in 2016 and 31,635 people in 2020 (Alle Cijfers, 2022). Combined, this would mean that the number of overweight people in 2016 and 2020 would be rounded 18,128 and 18,665 people respectively.



[6] A caveat to this data is that they are integers and probably rounded numbers while the model measures more precisely.

Figure 4.28 Base case result of people with overweight compared with historical values

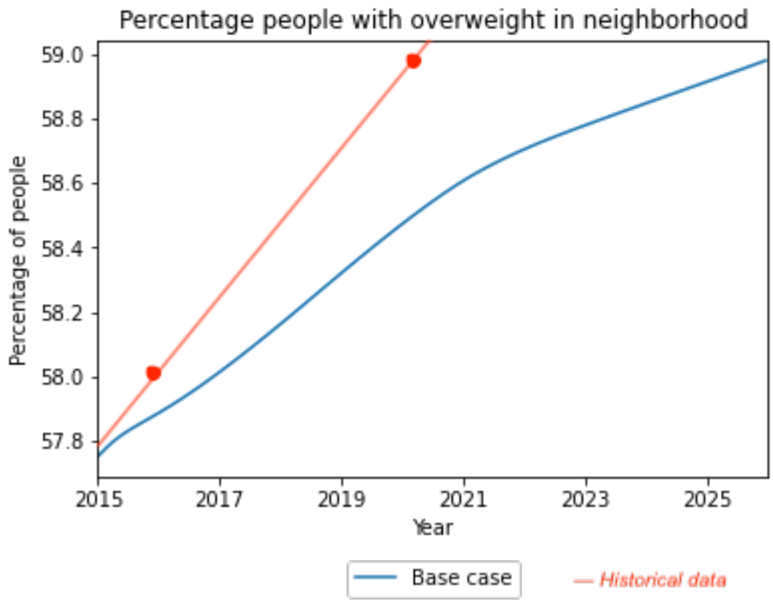


Figure 4.29 Base case result of percentage people with overweight in neighborhood compared with historical values

Figure 4.28 and 4.29 show the historical values compared to the model results. Similar to the historical values, the number of overweight people in the model increases, however, the increase in the historical value is steeper and the number of overweight people seems to be at 18000 instead of 18223. The cause responsible for this phenomenon concerns a difference in measure of the people with overweight by OpenInfo and AlleCijfers. Another reason for the difference of people with overweight resulting from the model compared to the historical value could lie in the way the population was modeled. The same growth rate for the population over time has been established for these data in the model while in reality there may be differences in the growth rate of the population each year. However, the reason for not modeling these small yearly differences is due to the objective of the model, which focuses on modeling the major trends.

The percentage of overweight people in the base case and the historical values are fairly similar. However, a steeper growth is observable here as well. Reason could be that the average energy imbalance in the model is quite low (between 1 and 3 kcal), and possibly higher in reality. In addition, as mentioned before, the data of OpenInfo and AlleCijfers does not correspond one-to-one. Another possible explanation could be the fact that OpenInfo rounded off the figures, while the model calculates with more decimals.

Although the model does not correspond one-to-one with values from history, the general trends between the model and reality do match.

4.3.7 Conclusion of model testing

The static and dynamic tests conducted in this section have provided more insight into the reliability of the model. The boundary adequacy showed that the right elements are included in the model, however, a more specific implementation of elements will further increase the reliability of the model. The model proved to be robust under most cases of extreme values tested, however, it is not compatible with extremely low values of population numbers because the lookup of the number of people with an ultra-processed diet does not allow for this. The sensitivity analysis indicated that the model exhibits explainable behavior for small changes in parameter values, increasing confidence in the model's behavior. The historical data validation revealed that the model behavior does not match one-to-one with historical value, but the general trends are correctly reflected in the model. Based on these tests, it can be concluded that the model is suitable for doing experiments with policy interventions in the Schildersbuurt to test the general trend of the effects of these interventions.

5. Evaluating local policies using the SD model

The final step in the modeling process involves applying interventions to the model to evaluate future effects (Sterman, 2000). Just as there is uncertainty about how overweight will evolve among the population over time, there are also uncertainties present in the model. To provide a complete picture of the situations that may occur in the future when policy interventions are introduced, these measures are tested under these uncertainties. A selection of policy interventions that seem or appear to be promising will be subjected to the model. Also, measures that are considered promising given the largest uncertainties will be identified.

The first section begins by uncovering the uncertainties and identifying those with the greatest influence on system behavior. Then, section 5.2 discusses the policy options and the meaning of their implementation for associated variables in the model. This is followed by sections 5.3, where the results of individual implemented interventions are given, and 5.4, in which results of combined interventions are discussed. The chapter closes with a conclusion in section 5.6.

5.1 Uncertainty analysis

Within the research area of overweight, there is still a considerable lack of data and information on the value of certain factors as well as the relationship between them. As a result, the model relies on several assumptions. Uncertainty analysis, unlike sensitivity analysis, is used to assess the influence of uncertain parameter input values on the systems behavior and to compare their impact (Morgan & Henrion, 1990). It involves the exploration of the impact of all uncertainties that may arise in the model (Pruyt, 2013). As a result, it provides an opportunity for scenario building (Kwakkel & Pruyt, 2013). Within this study, the model is tested for parametric uncertainty, which implies assessing the uncertainty of values of the parameters.

The inputs of parameters in the model were obtained from a wide range of sources from the literature. However, it cannot be said with certainty whether these values also represent the real value of a factor in the Schildersbuurt. First, this is because some inputs are based on studies from several years ago, in the meantime developments in society may have led to changes. In addition, not all studies from which data was obtained are specifically focused on the Dutch population, cultural differences may underlie differences in findings between countries. In some cases, calculations had to be made based on information from different sources to arrive at a parameter input. These studies usually do not have the same setup, so in this case, the calculations made for the model may not be accurate. Moreover, the model relies on various assumptions, such as assumptions made in the case of various assertions of studies about the same phenomenon. Assumptions have also been made for parameters whose value could not be deduced from the literature on a one-to-one basis. The aforementioned causes lead to uncertainty about the input of parameters to the model, these parameters have been included in the uncertainty analysis and are the following:

- *Additional physical activity per unit increase of social cohesion*
- *Avg. MET value during NEAT activities*
- *Walking time*
- *Cycling time*
- *Avg. MET value of sport activities*
- *Decrease in minutes per day spent on activity per kg increase in weight*

- *Reduced expense on kcal per reduced number of minutes per day on activity*
- *Ratio physiologically determined intake*
- *Degree of underreporting in food consumption survey*
- *Annual increase of unhealthy food suppliers*
- *Dutch average ratio of people having an ultra-processed diet*

The uncertainty analysis tests parameters in the range of possible values, the adjustments to the model for performing the test are given in appendix E.1.

The results of the uncertainty analysis show that the sensitivity of the behavior of the KPIs to changes in *additional physical activity per unit increase of social cohesion* is small. As Figure[7] 5.1 illustrates, there is almost no variation in the outcomes for the KPIs at different values of the parameter. This is a major difference compared to the results in Figure 5.2, which shows that the KPIs are very sensitive to changes in the *avg. MET*[8] *during NEAT*[9] *activities*. From the results of the other uncertainty tests shown in appendix it becomes clear that the KPIs are not sensitive to changes in the values of the parameters, except for changes in the parameter of *avg. MET value of sport activities*. The values within the chosen range for the parameter *avg. MET value of sport activities* could potentially increase or decrease the *percentage of people with overweight in the neighborhood* by about 2.5 percent.

The explanation for why these parameters produce large effects in model behavior is firstly because the *avg. MET during NEAT activities* is a large determinant of *avg. energy expenditure on non-exercise related activity*, which is a key determinant of expenditure during activity thermogenesis. Regarding the avg. *MET value of sport activities*, it affects the *avg. energy expenditure during sport activity*. Although expenditure during sport activity is not directly a large determinant of total energy expenditure, the large differences of the tested values compared to the base case cause large observable differences in the KPI values. This wide range of values is due to the high variance of expenditure during sport activity.

[7] The figures are displayed in Vensim because the data of the sensitivity analysis could not be stored and accessed with other data analysis programs such as Python or Excel. It is not possible to adjust the unit of the y-axis of the figures in Vensim to years given the chosen time unit of the model in days. It is therefore important to note that day 0 corresponds to January 1, 2015 and day 4000 to December 31, 2025. Moreover, the scale is the same for each graph so that differences between parameters become apparent (of relevance in this analysis)

[8] MET = Metabolic Equivalent of Task

[9] NEAT = Non-exercise related activity thermogenesis

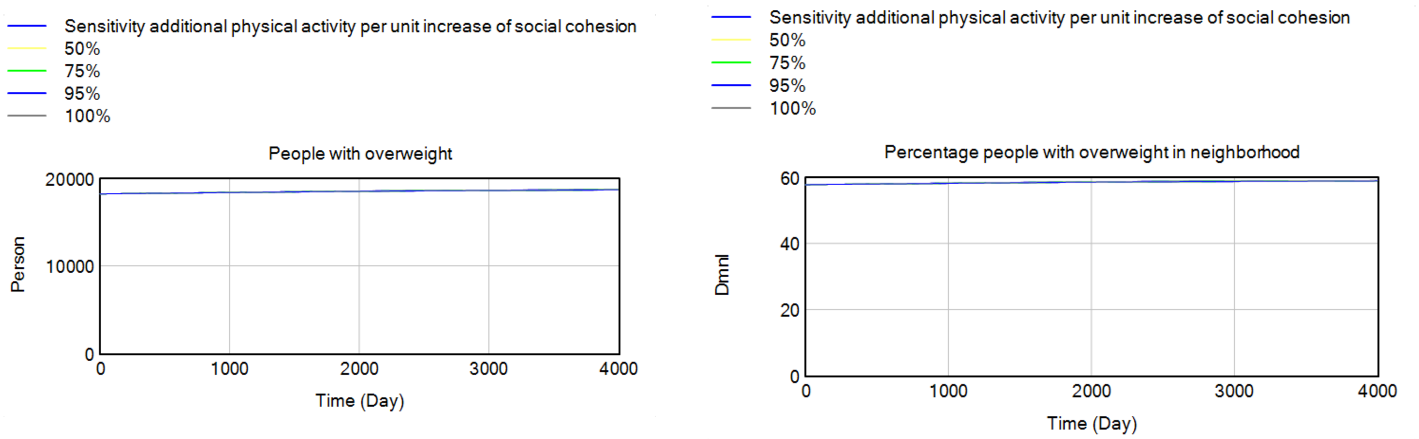


Figure 5.1 Sensitivity additional physical activity per unit increase of social cohesion

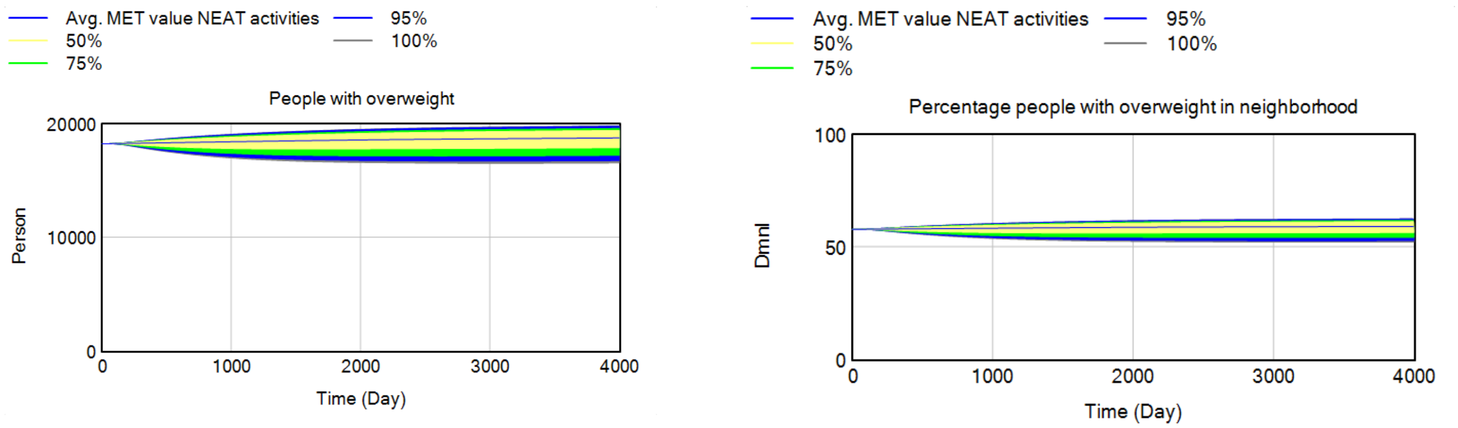


Figure 5.2 Sensitivity avg. MET value during NEAT activities

As a result of the sensitivity of the KPIs to the parameters *avg. MET value during NEAT activities* and *avg. MET value of sport activities*, the effects of policy interventions could potentially be lower or higher compared to when testing at the assumed base case model values. Therefore, the effects of the proposed policy options will be tested under the uncertainty of these variables. Since these two parameters cause fluctuations in the model output, during the process of selecting policy interventions attention will also be paid to measures that affect these parameters as they have the potential to have a large impact.

The direction of both avg. MET values cause the same behavior. A low value will in both cases result in low energy expenditure and therefore a large energy imbalance, which increases overweight. The reverse is true for high values of the avg. MET values. Therefore, two scenarios are considered important to give a clear picture of the possible range in which the effects of policy options will occur. The first scenario focuses on the situation in which low values of the avg. MET values occur, the second on high values. An overview of the possible scenarios is presented in Table 1.

Table 1. Scenarios resulting from the uncertainty analysis

Scenario \ Parameter	Avg. MET[10] value during NEAT[11] activities	Unit	Avg. MET value of sport activities	Unit
Low level of activity	0.6	Dmnl[12]	6.0	Dmnl
High value of activity	1.0	Dmnl	8.5	Dmnl

5.2 Identification on policy interventions

In recent years, there has been increasing attention to what actions can be taken to address overweight at the local level. A wide variety of interventions have been developed and applied in neighborhoods throughout the Netherlands. The most promising policies will be implemented on the model in order to investigate their effect on the Schildersbuurt. Perhaps more policy interventions will have potential to be applied in the Schildersbuurt which cannot all be tested on the model within this research. However, the analysis of the model provides insight into the possible future situations that can arise when implementing the introduced policy measures and their effectiveness. The purpose of this section is to identify these. It serves as a starting point for analyses of other possible policies. First, it will be explained which policy interventions from the literature are found to be most effective and how they would affect the model. It is important to note that all measures are introduced after 5 years, so on day 1825 of the simulation[13]. Next, two more policies are discussed that seem valuable given their direct impact on uncertain factors, thus having the potential to achieve the desired effect.

5.2.1 Policy 1 - Lifestyle as medicine

A growing body of research points to the importance of a combined approach to overweight interventions (Brink et al., 2021; Seidell et al., 2022). A long term national program is focusing on reduction of overweight in children (JOGG, n.d.). However, for adults, only two national programs have been established recently for 1) overweight and 2) type-2 diabetes. Partnership Overweight Netherlands (PON) has been commissioned by the Ministry of Health to translate the network approach to overweight children into a network approach to overweight adults (Partnerschap Overgewicht Nederland, n.d.). TNO and PON together are developing several policy advice support tools to support the local policy makers and healthcare providers with decision support tools (H.M. Wortelboer, personal communication, August 3, 2022), but no data are available yet.

An example of a foundation focusing on an integrated network approach is Lifestyle for Health in which various experts from both the medical and scientific fields work together (Lifestyle4Health, n.d.). Under the umbrella of this foundation, several initiatives and research projects have taken place in different places. For example, in the village of Leende, efforts are being made to increase food knowledge and healthy food offerings by fast food suppliers (GezondDorp, n.d.). In the Stevenshof neighborhood in the city of Leiden, a project was conducted in 2019 with 15 participants under the

[10] MET = Metabolic Equivalent of Task

[11] NEAT = Non-exercise activity thermogenesis

[12] Dmnl = Dimensionless

[13] To adjust the values of the affected variables, IF THEN ELSE functions are applied that cause this variable to change the value to policy value after day 1825.

name of ‘Diabetes and lifestyle as medicine (DLAM)’. This started with a so-called '360 degree diagnosis' in which a person was examined for all kinds of physiological values. After that, a personalized lifestyle program was drawn up whereby the patient was also supervised. After a few months the 360 degree diagnosis was repeated. It appears to be a useful approach, however, a roadmap still needs to be developed so that this measure can be practically applied (Lonkhuyzen, 2022). In the city of Zwolle, an integrated and personalized obesity coaching program was set-up in 2018, focusing on the reduction of overweight of adults in a rehabilitation center (Brink et al., 2022). In the municipality of Helmond, citizens are walking together within the initiative 2diabeat, and monitoring of the effects has only recently started (Tilburgs, 2021).

Many of these projects focus on a combination of healthy eating and exercise, in particular stimulating lower levels of activity like walking and cycling (GezondDorp, n.d.; Tilburgs, 2021). For example, healthy eating is encouraged in the Gezond Dorp project in Leende by organizing cooking clinics and information meetings with experts (GezondDorp, n.d.). For the application of the Lifestyle as medicine policy the project in Leende is taken as a reference and therefore the implementation will focus on nutritional knowledge and walking time. However, there is still not much local policy and effect data available on the extent to which factors are influenced by the different local programs, such as the one in Helmond. Therefore, a range of values in which the measure may have an impact on corresponding variables is used. The nutritional knowledge values are lowered because in the model this value is multiplied by the energy intake so a lower value will lead to a lower energy intake. The new values for nutritional knowledge are ranging from 0.98 to 0.99 and similarly for all subscripts, i.e. each educational level. This value seems low, however it is the percentage of the largest determinant of total avg. intake which means that a small difference in nutritional knowledge can have a significant impact on the overall model behavior. The range for the increase of the values for walking time per week is set to 5-10 minutes for all ethnic groups. Table 2 indicates a clear overview of these ranges.

Table 2. Parameter adjustment by implementation of policy 1 - Lifestyle as medicine

Parameter	Unit	Subscripts	Current value	Policy value range
Nutritional knowledge	Dmnl	Level of education [low, intermediate, high]	1, 1, 1	0.98, 0.98, 0.98 - 0.99, 0.99, 0.99
Walking time	Min/Week	Ethnic group [Dutch, Western, Moroccan, Surinamese/Antillean, Turkish, Other Non-Western]	64, 66, 58, 58, 58, 58	69, 71, 63, 63, 63, 63 - 74, 76, 68, 68, 68, 68

Given the range of values chosen in the implementation of this measure, the simulations will refer to low values and high values. Low values for policy 1 means that within the chosen range the lowest energy intake is caused and so of the chosen range the lowest value is implemented for cycling time and the highest value for nutritional knowledge. The reverse is true for high values of policy 1. Table 3 shows the implementation for policy 1 with low and high values.

Table 3. Low and high values of policy 1 implementation - Lifestyle as medicine

	Nutritional knowledge [low, intermediate, high]	Walking time [Dutch, Western, Moroccan, Surinamese/Antillean, Turkish, Other Non-Western]
Low values for policy 1	0.99, 0.99, 0.99	69, 71, 63, 63, 63, 63
High values for policy 1	0.98, 0.98, 0.98	74, 76, 68, 68, 68, 68

5.2.2 Policy 2 - Revised environmental law

The availability of unhealthy food in the environment has increased significantly in recent years (Mackenbach, 2016; Nieuwsuur, 2021; Pointer (KRO-NCRV), 2021). Municipalities wish to halt this strong growth of unhealthy food businesses in neighborhoods however they have no legal authority to do so (van Kolfschooten et al., 2020). Within the environmental law as it is now enacted, entrepreneurs are free to start a new business regardless of the available supply. However, municipalities would like to have a tool to deny the permit based on the already present supply in the municipality. To achieve this, the national government could amend the Environment Act (Blokhuis, 2021).

If the Environment Act is amended, the municipality of The Hague could decide to no longer allow new unhealthy food suppliers to be established in the Schildersbuurt. The variable *annual annual increase of unhealthy food suppliers* in the model then becomes zero, see Table 4.

Table 4. Parameter adjustment by implementation of policy 2 - Revised environmental law

Parameter	**Unit**	**Subscripts**	**Current value**	**Policy value**
Annual increase of unhealthy food suppliers	Supplier/Year	-	0.5	0

5.2.3 Policy 3 - Improving bicycle network

The Dutch government has set itself the goal of making the country more bicycle-friendly (Ministry of Health, Welfare and Sport, n.d.). Throughout the country, several projects have been seen in recent years where, for example, bicycle paths have been made safer and so-called bicycle highways, fast connections between certain places, have been constructed (Fietsersbond, 2018). Municipalities can improve the bicycle network in their neighborhoods to stimulate bicycle use and associated health benefits. RIVM (2006) conducted research into which local policies are most effective in countering obesity. In the results of the study attractive and safe walking and cycling paths were also mentioned as adequate measures. According to residents, the bicycle network in the Schildersbuurt is not optimal (Zandvliet et al., 2012). Recently a plan has been drawn up to improve the bicycle paths in the neighborhood, but this plan still encounters some bottlenecks. These grounds indicate that the measure of improving bike paths in the Schildersbuurt is suitable for simulation in the model. The measure responds to the parameter of bicycle use, of which table 5 gives the adjusted values. Again, a range of values has been chosen as precise data of this potential plan is not available. Evaluations of projects of improved bicycle infrastructure show that 2 to 5% of the people on the new infrastructure used to take the car for that route (Rijkswaterstaat, n.d.). Nijland and Van Wee (2006) state that reducing the travel time by means of bicycle policy may lead to 3% higher bicycle use. Based on these sources a range of between +2 and 5% of time spent cycling has been chosen for implementation, these values are shown in Table 5.

Table 5. Parameter adjustment by implementation of policy 3 - Improving bicycle network

Parameter	**Unit**	**Subscripts**	**Current value**	**Policy value range**
Cycling time	Min/Week	Ethnic group [Dutch, Western, Moroccan, Surinamese/Antillean, Turkish, Other Non-Western]	78, 70, 52, 52, 52, 52	80, 71, 53, 53, 53, 53 - 82, 74, 55, 55, 55, 55

5.2.4 Policy 4 - Eurofit in neighborhoods

It would be interesting to introduce measures which focus on stimulating physical activity during the day in view of the uncertainty analysis that revealed that the behavior of the KPIs is sensitive to small changes in the parameter value of *avg. MET*[14] *value during NEAT*[15] *activities.* Moreover, several studies are pointing out the consequences of sedentary behavior on our health, for example, it is associated with obesity and cardiovascular disease (Chau et al., 2013; Petersen et al., 2014). In addition to measures to motivate sport, there are also more measures nowadays aimed at encouraging physical activity during the day, in the model this is covered by the variable non-exercise related activity. One of these non-exercise related activity programs at the neighborhood level is 'Gezond in de buurt in beweging' in which citizens are encouraged to exercise more during the day, the emphasis is not only on sports, but taking the stairs more often, for example, is also promoted. Moreover, during this program an information session is held by a dietician to point out the importance of a healthy diet. The measure is mainly targeted at people with a low economic status. This program was evaluated as effective by an independent party (Leemrijse et al., 2011).

The RIVM has created a website to help policymakers choose policy interventions, naming different interventions and their demonstrated effectiveness. A similar intervention is mentioned here, called EUROFIT. This is a lifestyle intervention that focuses on both healthier eating and more exercise. The target group of the measure was soccer supporters, but can also be expanded to people with a low socio-economic status (Van Nassau & Geubbels, 2022).

Precise data on the results of these measures are unknown but assumptions (a range of values) will be made to test a similar kind of intervention for the purpose of this study. This kind of intervention will similarly affect kcal intake by diet and kcal expenditure by non-exercise related activity. Given that those kinds of policies target people with a low SES, only the *nutritional value* of the group with a low education level will be adjusted. The other variable related to this intervention is the *minutes spent on non exercising activity per day by person in neighborhood.* Since this is an endogenous obtained

[14] MET = Metabolic Equivalent of Task

[15] NEAT = Non-exercise related activity thermogenesis

variable, an extra variable will be modeled and added to this endogenous variable in order to complete the adjustments, see Table 6. Similarly to policy 1, these values can be divided into two scenarios, as shown in Table 7.

Table 6. Parameter adjustment by implementation of policy 4 - Eurofit in neighborhoods

Parameter	**Unit**	**Subscripts**	**Current value**	**Policy value range**
Nutritional knowledge	Dmnl	Level of education [low, intermediate, high]	1, 1, 1	0.98, 1, 1 - 0.97, 1, 1
Extra minutes per day spent on non-exercise related activity due to policy 4	Min/Day	-	-	5 - 10

Table 7. Low and high values of policy 1 implementation - Lifestyle as medicine

	Nutritional knowledge [low, intermediate, high]	Extra minutes per day spent on non-exercise related activity due to policy 4
Low values for policy 1	0.98, 1, 1	5
High values for policy 1	0.97, 1, 1	10

5.2.5 Policy 5 - Building an outdoor gym

Other measures that could be interesting in light of the results of the uncertainty analysis are those that focus on encouraging sports activity.

The WHO European Healthy Cities program was established in 1986 to assist in the local implementation of the WHO strategy for Health for all. In a planning guide, they provided cities with advice on how policy makers could make the city more active (Edwards, & Tsouros, 2008). Several countries have taken the lever in recent years to implement this advice. For example, the number of outdoor sports parks in Australia and Portugal has increased significantly in recent years (Levinger et al., 2018; Municipality of Porto, 2022). Verdonk and Van Koperen (2007) who wrote a report with ideas to make Dutch neighborhoods healthier also encourage to organize the neighborhood in such a way that activity is encouraged, of which such public sports parks can be an example. This measure therefore aims to place more fitness equipment in public parks.

According to research from Canada (Copeland et al., 2017), about 20% of the adults in the group studied use such facilities with some regularity, most of them several times a week. Therefore, for the implementation of the policy measure in the current model, 2 times a week was assumed for the use of the facilities. According to Chow et al. (2017), people who use them spend on average about 9 minutes on the devices. In total, this would amount to 18 minutes per week in this study. Based on this information, the values for time spent on sport activities by ethnic groups were adjusted for this policy intervention[16], this is shown in Table 8.

Table 8. Parameter adjustment by implementation of policy 5 - Building an outdoor gym

Parameter	Unit	Subscripts	Current value	Policy value
Avg. hours per week of sport activities	Hour/Week	Ethnic group [Dutch, Western, Moroccan, Surinamese/Antillean, Turkish, Other Non-Western]	1.03,1.03,0.99, 1.05,0.83,0.96	1.09, 1.09, 1.05, 1.11, 0.89, 1.02

5.3 Effect of individual interventions under uncertainties

As shown by the uncertainty analysis, the variables *avg. MET value of sport activities* and *avg. MET value during NEAT activities* have a large impact on the system. Therefore, the robustness of the selected policy interventions will be tested under the uncertainty margins of these variables. The possible uncertain values of these variables are summarized in scenarios called low activity and high activity and the simulation outputs of each of the policies in these scenarios will be discussed below.

[16] 18 minutes per week relates to 0.3 hours and it involves 20% of the population so together that comes to an average of 0.06 hours of sport activity across the population.

5.3.1 Model outcomes policy 1 - Lifestyle as medicine

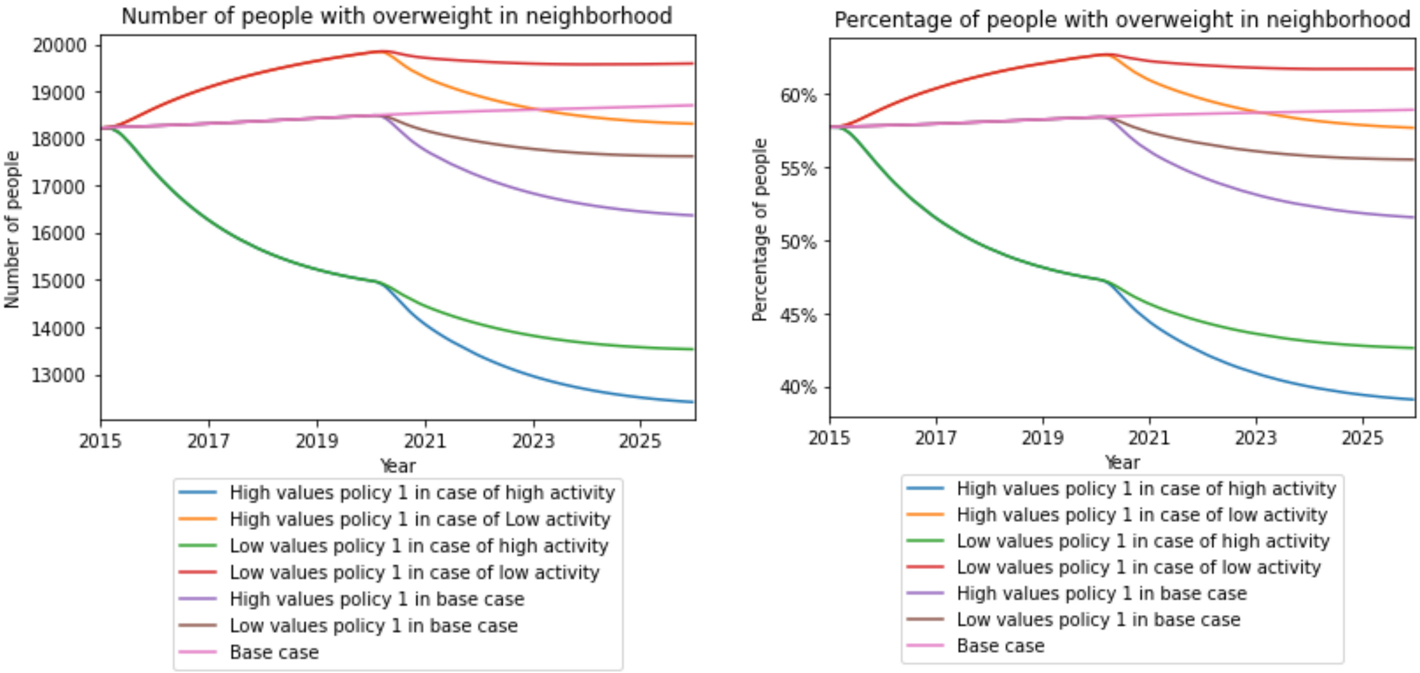


Figure 5.3 Model outcomes policy 1 - Lifestyle as medicine

The 7 lines in the graph of Figure 5.3 in essence show the range in which this policy can have an effect under the uncertainties present. In this case, that range would be between the highest and lowest values given at 'low values policy 1 in case of low activity' and 'high values policy 1 in case of high activity' respectively resulting in 12500 and 19500 people being overweight by the end of 2050. As can be deduced from Figure 5.3, the uncertainties have a major impact on the KPI outcomes. Nevertheless, it can also be seen that policy 1 has a significant influence on the development of overweight in the neighborhood. Especially in case of high values for policy 1, this intervention has the potential to address overweight locally. In the base case this policy could lead to a reduction of the *percentage of people with overweight* from around 59% to either 55% (in case of high values for this policy) or 50% (in case of low values for this policy).

The reason this policy has such an effect is firstly because it acts on both reducing energy intake and increasing energy expenditure, thus counteracting a positive energy imbalance. In addition, the *nutritional knowledge* has an effect on a major determinant of *total avg. energy intake*, namely the *kcal intake from food and non-alcoholic drinks. Walking time*, while having a smaller impact on the overall behavior of the system, does increase *avg. energy expenditure during activity thermogenesis* hence contributes to an increase in *total avg. energy expenditure*.

5.3.2 Model outcomes policy 2 - Revised environmental law

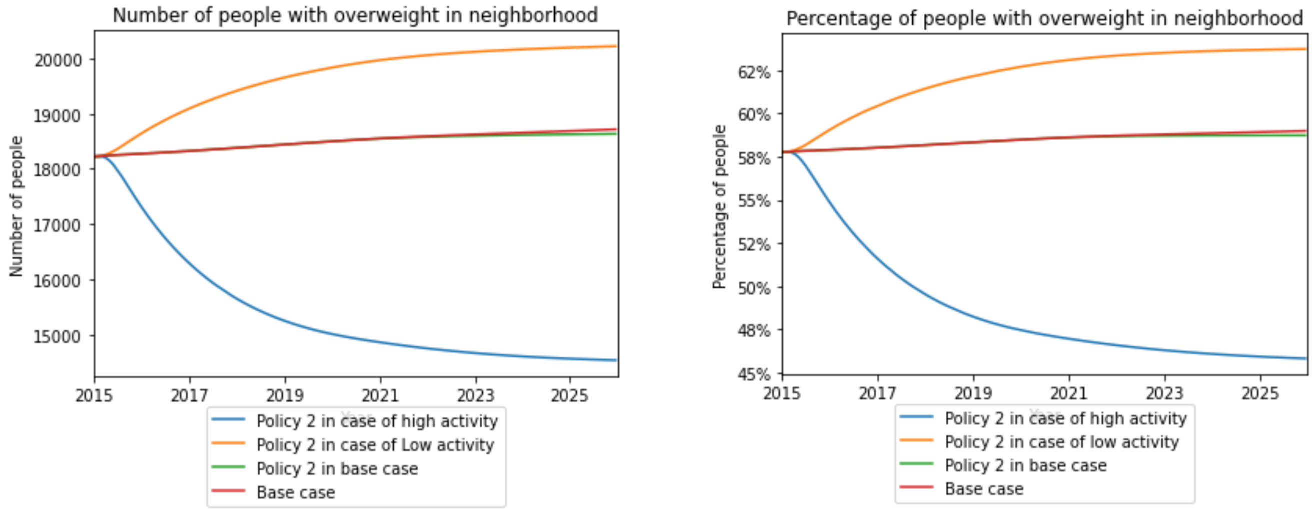


Figure 5.4 Model outcomes policy 2 - Revised environmental law

As shown in Figure 5.4, the policy measure 'revised environmental law' seems nearly to have an effect on the model behavior of the KPIs in case of high or low activity. Further inspection on the model reveals that the policy does have a small influence on the system's behavior, the major uncertainties, the effect on the KPIs is negligible. The implementation of policy 2 in the base case shows a difference of about -0.3% in the percentage of overweight people in the neighborhood compared to the base case. Policy 2 decreases *total avg. energy intake* by decreasing the value of *extra kcal consumed due to ultra-processed diet on average*. The policy is powerful enough to reduce the positive energy imbalance to a fraction below zero. However, this is to a minimal extent, hence the number of overweight people in the population decreases marginally. In conclusion, policy 2 does not seem to be a very effective policy intervention for combating overweight in the Schildersbuurt.

5.3.3 Model outcomes policy 3 - Improving bicycle network

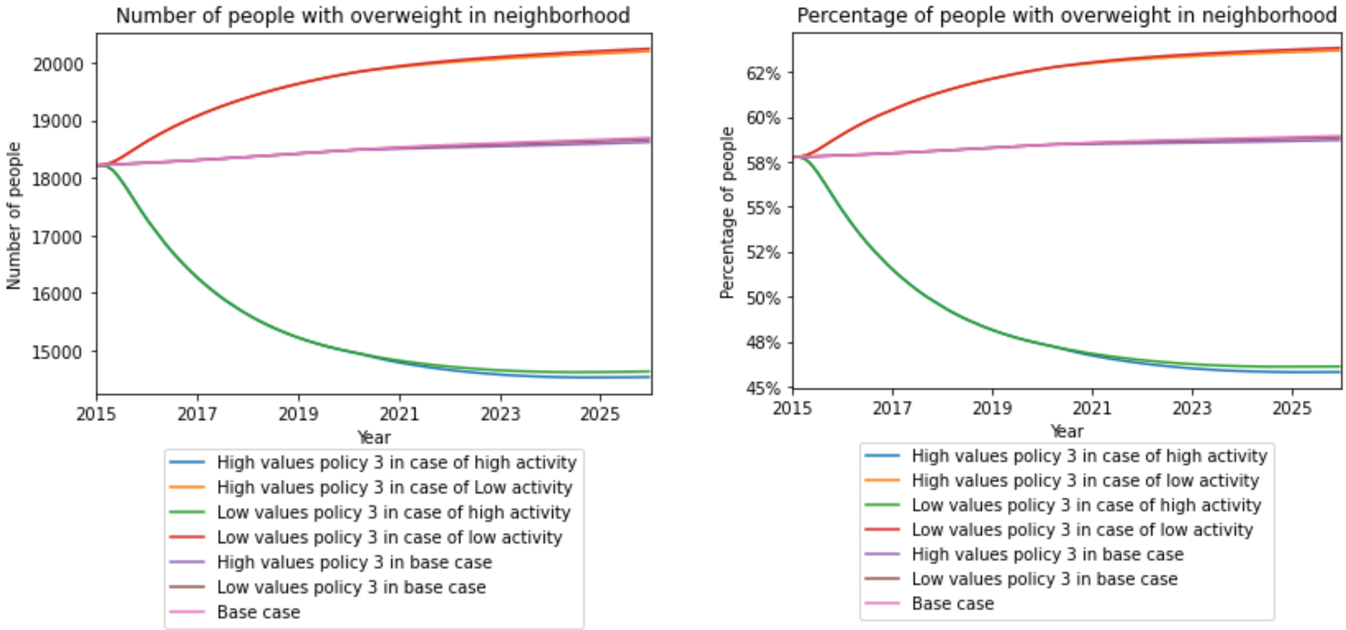


Figure 5.5 Model outcomes policy 3 - Improving bicycle network

The effect of policy measure 3, improving bicycle networks, in the model is presented in Figure 5.5. Similar to the implementation of 'revised environmental law' in the model, there is almost no observable effect of this intervention under the identified uncertainties. Also, low and high values of this intervention are difficult to distinguish. The measure increases the amount of energy consumed during activity. However given the small increase in cycling minutes with this measure it does not cause a significant change in total expenditure. Therefore, the *total avg. energy expenditure* does not outweigh the *total avg. energy intake*. As a result, it can be stated that this intervention is not like have persuasive capability to set the course of overweight in the desired direction based on the model outcomes.

5.3.4 Model outcomes policy 4 - Eurofit in neighborhood

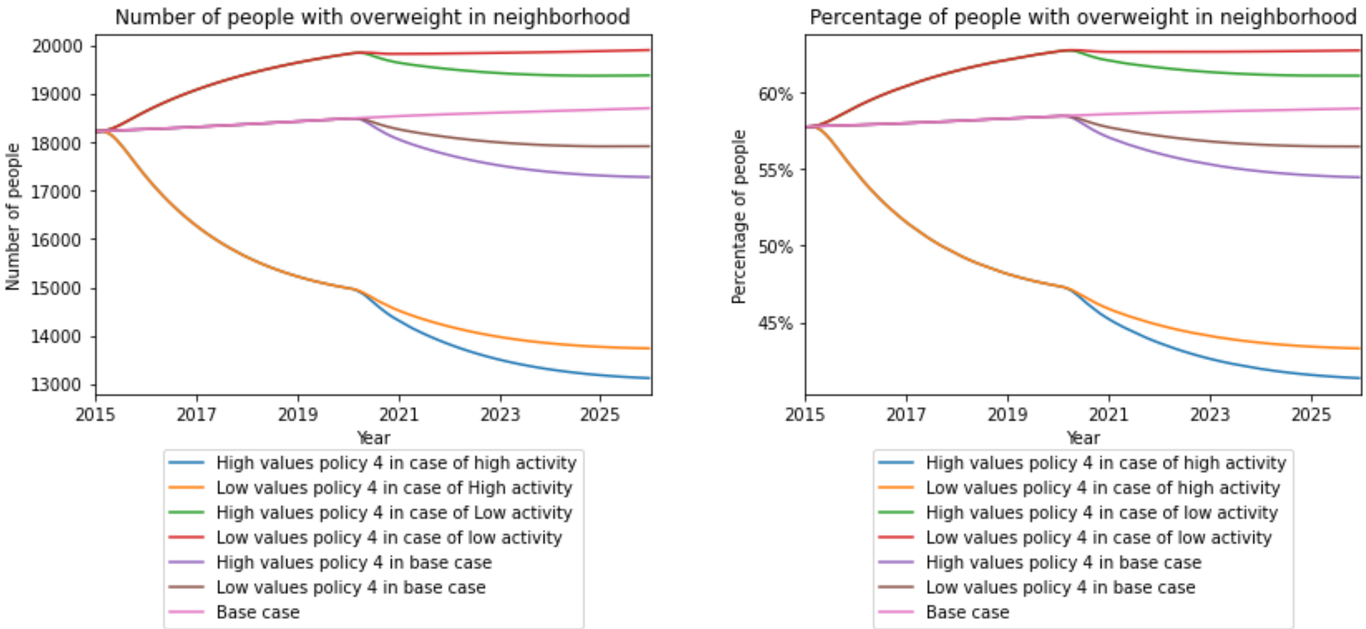


Figure 5.6 Model outcomes policy 4 - Eurofit in neighborhood

Based on the model, the results of the policy 4, Eurofit in the neighborhood, as depicted in Figure 5.6 seem promising. Both the low values and the high values of the selected range of this measure show a change in the course of overweight in the population upon the introduction of the measure into the model. The underlying argument for this behavior again comes from an impact on both increase in energy expenditure and decrease in energy intake. The change in nutritional knowledge causes a significant decrease in *avg. daily energy intake from food and non-alcoholic* drinks. The increase in non-exercise related activity leads to higher expenditure during activity. The high values of this policy have a considerably larger effect than the low values. In conclusion, this policy intervention has possibly a beneficial effect on the rate of overweight in the local population.

5.3.5 Model outcomes policy 5 - Building an outdoor gym

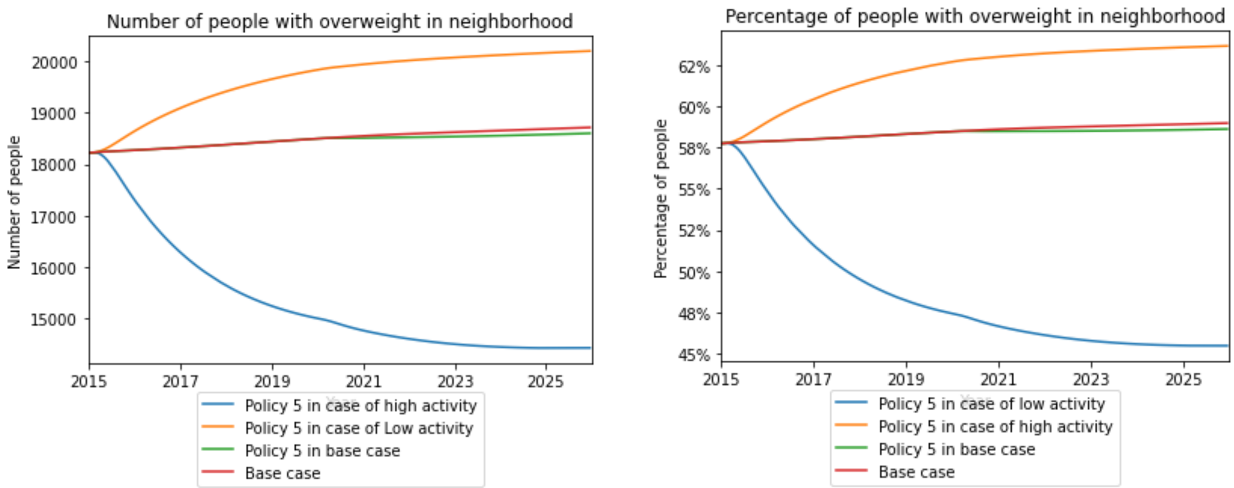


Figure 5.7 Model outcomes policy 5 - Building outdoor gyms

As shown in Figure 5.7, there is a small change in course direction observable in the graph of 'policy 5 in case of high activity', this is because there is a bigger difference between the values of the high activity scenario compared to the one of low activity. Measures aimed at increasing sport activity have potential to decrease the degree of prevalence of overweight in the population because sport activity is an important determinant of energy burned due to activity thermogenesis. However, this particular measure has too slight an effect on increasing sports activity, making it insufficient for a course change in the number of overweight people in the neighborhood.

5.4 Potential of combined interventions under uncertainties

The impact of individual policy interventions varies widely. The model shows that the integrated approach of different disciplines offers the most potential for reducing overweight at the neighborhood level in the Schildersbuurt. In addition to individual measures, local policy makers can also introduce a set of measures so that the desired outcome has a higher probability of succeeding because a set of measures offers the ability to approach the problem from multiple angles. Also, policy measures can have a reinforcing effect on one another.

5.4.1 Implementation of combined interventions

The measures that, according to the model simulations, achieve the results that come closest to the desired objective are 'policy 1 - Lifestyle as medicine' and 'policy 4 – Eurofit in the neighborhood'. A combination of these two measures therefore has potential to cause a preferred performance of the KPIs in the model. The change of the parameter values for the implementation of these policies and the combination in which these adjustments are implemented are shown in Table 9 and Table 10, respectively.

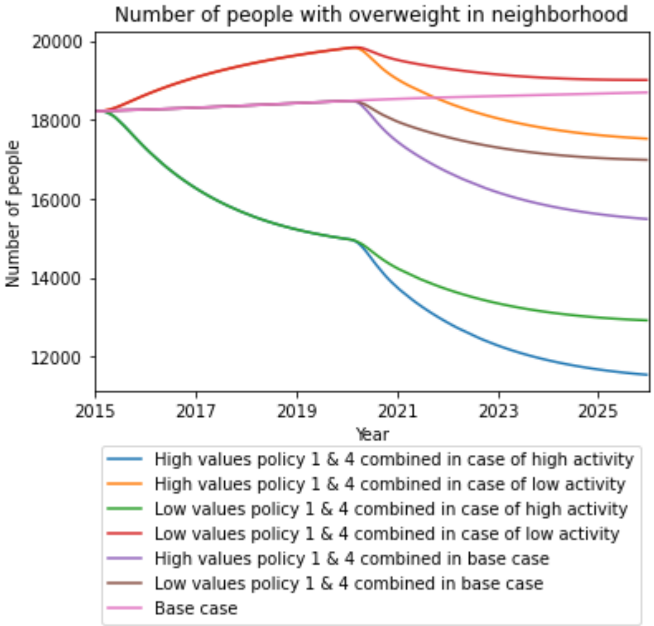
Table 9. Parameter adjustment by implementation of policy 1 and 4 combined

Parameter	**Unit**	**Subscripts**	**Current value**	**Policy value range**
Nutritional knowledge	Dmnl	Level of education [low, intermediate, high]	1, 1, 1	0.96, 0.98, 0.98 - 0.97, 0.99, 0.99
Walking time	Min/Week	Ethnic group [Dutch, Western, Moroccan, Surinamese/Antillean, Turkish, Other Non-Western]	64, 66, 58, 58, 58, 58	69, 71, 63, 63, 63, 63 - 74, 76, 68, 68, 68, 68
Extra minutes per day spent on non-exercise related activity due to policy 4	Min/Day	-	-	5 - 10

Table 10. High and low values of policy 1 and 4 implementation

	Nutritional knowledge [low, intermediate, high]	Walking time [Dutch, Western, Moroccan, Surinamese/Antillean, Turkish, Other Non-Western]	Extra minutes per day spent on non-exercise related activity due to policy 4
Low values for combined policies	0.98, 0.99, 0.99	69,71,63,63,63,63	5
High values for combined policies	0.97, 0.98, 0.98	74,76,68,68,68,68	10

5.4.2 Effect of combined interventions



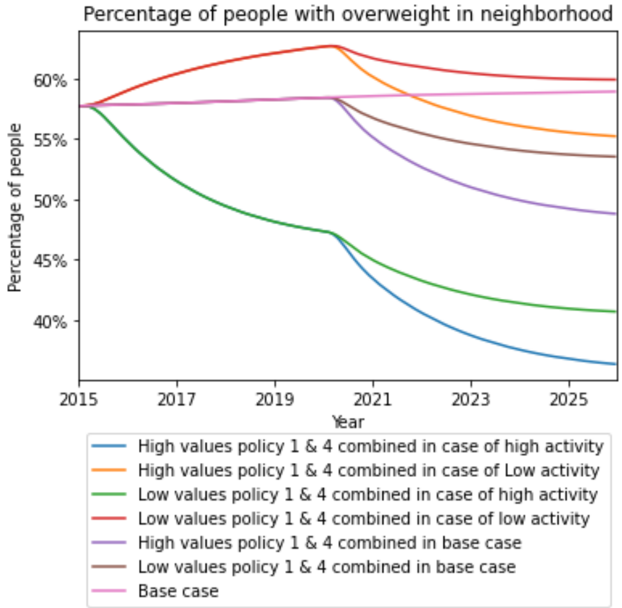


Figure 5.8. Model outcomes of policy 1 'Lifestyle as medicine' and policy 4 'Eurofit in neighborhoods' combined

The combination of the implemented measures 'lifestyle as medicine' and 'Eurofit in the neighborhood' in the model show favorable results. The shape of the graphs of Figure 5.8 correspond to the shape of the individual interventions, however, the effect is now stronger. A combination of these two measures could lead to a reduction of overweight people in the most favorable case, up to 40% of the overweight population. In the least favorable case, i.e. low values for the combined intervention values and a low level of activity of people will result in a 60% rate of overweight people 5 years after introduction of the measures.

5.5 Conclusion

This chapter exposed the uncertainties of the model and determined the ones with major impact on the system's behavior. Subsequently, based on the literature and uncertainties, five interventions with potential to reduce overweight at the local level were selected. The five measures were each first tested individually under the largest possible uncertainties that could arise. Measures that address both increasing energy expenditure and decreasing energy intake appear to be the most effective, as they generate the most substantial change in energy imbalance. Policy measures focused on influencing *nutritional knowledge* are capable of reducing the *avg. daily energy intake from food an non-alcoholic drinks* and thus the *total avg. energy intake*. Measures that exert a minor influence on expenditure during activity, such as cycling time at policy 3, are not sufficiently powerful to increase *total avg. energy expenditure* to the same level as *total avg. energy intake* that was observed. Hence, they cannot accomplish the desired effect, an energy imbalance of zero or lower. The same applies to policies where total energy intake is reduced but with an insufficient number of kcal to reach below the level of *total avg. energy expenditure*, as in policy 2.From these findings, the measures with an integrated approach ‘Lifestyle as medicine’ and ‘Eurofit in the neighborhood’ were found to yield the most desired results. A combination of the two was then also tested on the model in order to be able to provide proper policy advice for local policy makers.

Chapter 6. Conclusion, limitations and recommendations

This closing chapter will formulate an answer to the main research question stated in Chapter 1. The major insights of the study will be elaborated on. Also, the relevance of the research, as well as its limitations will be clarified. In addition, this chapter provides recommendations for follow-up research.

6.1 Overview of the research findings

This study aimed to gain more insight into the factors that influence overweight. Given the delegation of the responsibility of combating health issues from the national government to municipalities (Ministry of Health, Welfare and Sport, 2018) as well as the potential for an integrated approach of different disciplines and health care providers (Brink et al., 2022), a neighborhood perspective was chosen. A system oriented approach seemed to be the most appropriate, and System Dynamics (SD) was deployed as a modeling method. The dynamics of the elements in the system as well as the effects of possible policy interventions could be examined using this method (Sterman, 2000).

A causal relationship diagram (CLD) of the factors influencing overweight at an individual level has been prepared by a collaboration of the Dutch scientific research organization TNO for applied sciences (TNO) and Partnerschap Overgewicht Nederland (PON). This CLD model functioned as a basis for derivation of certain mechanisms on the neighborhood level. In addition, a literature review was conducted for retrieving information in order to model neighborhood factors related to overweight which was central in the current study. Data from the Schildersbuurt in the Hague was chosen for implementation to the model in this study. The data was obtained from different data sources, such as scientific studies on specific elements or relationships regarding factors of overweight as well as data sources from the municipality of the Hague (https://denhaag.incijfers.nl). Creating a (qualitative) model concerns an iterative process. A renowned professor of nutrition and health (J. Seidell) was consulted during the process for feedback, which was implemented to improve the structure of the model. For the establishment of the quantitative model, functions for the parameters in the qualitative model were implemented. To test the models ability to simulate real world behavior in order to do experiments with policy interventions, validation and verification tests were performed. Given that many assumptions had to be made, an uncertainty analysis was conducted exposing the main uncertainties of the model. As a last step, relevant policy measures were tested under these uncertainties in order to demonstrate policy implications of possible future conditions.

The research question that was central to this study concerns:

What combination of local policy interventions can be deployed to reduce overweight at the neighborhood level?

Becoming overweight happens as a result of fat storage in the body, which occurs when there is an imbalance of energy intake and energy expenditure (Hill, 2006; Fallah-Fini et al., 2021). Energy imbalance refers to a value at the individual level. To determine overweight prevalence at the neighborhood level, it was concluded that a translation of the average energy imbalance per person to the degree of overweight among the population needed to be made. As a result, neighborhood level modeling was performed using the sub-models, 1) energy intake, 2) energy consumption and 3) degree of overweight among the population. Characteristic for complex systems modeled with SD are feedback structures (Sterman, 2000), structures that have a self-reinforcing or balancing effect, several of which were identified in the model. Weight, for example, was found to influence metabolism which in turn influences weight (Henry, 2005). Within the submodel of energy intake was distinguished between intake by food and non-alcoholic beverages, alcohol consumption and as a result of the food environment. Due to differences in determining determinants, such as ethnicity and socioeconomic status. The submodel of energy expenditure identified the three mechanisms in the body responsible: activity thermogenesis, food-induced thermogenesis and resting metabolism. Ethnicity here was found to be an important determinant of energy expenditure as it affects both walking, cycling and also sports activity, which are all part of activity thermogenesis.

Simulations of the model indicate that overweight in the neighborhood of the Schildersbuurt will continue to increase in the coming years from 58 percent in 2015 to around 60 percent in 2025, when no policies targeting weight gain are introduced (i.e., base case simulation). Based on the literature, it was concluded that the following five interventions may have potential for reducing overweight at the local, neighborhood level:

- *Lifestyle as medicine*: an intervention in which people are encouraged to walk more as well as being educated about healthy food, increasing their knowledge about this topic.
- *Revised environmental law*: a change in legislation allowing municipalities to prohibit the establishment of unhealthy food suppliers in specific areas.
- *Improving bicycle network*: improving the bicycle infrastructure in the neighborhood which invites people to cycle more.
- *Eurofit in the neighborhood*: An integrated lifestyle intervention that targets the food intake of people with low socioeconomic status (SES) and also stimulates the daily activity of people in the neighborhood.
- *Building an outdoor gym*: facilitating public fitness equipment with the aim of increasing people's sports activity.

The model is characterized by uncertainties because of the fact that it is unknown how certain factors will evolve over time or how they affect model behavior. To provide complete information of the possible effects in implementing these measures, uncertainties in the model, such as the average weekly walking time or the growth of unhealthy food suppliers in the neighborhood, should be taken into account. Since the model is based on assumptions, uncertainties in the model could distort the effects of the policies performance when applied to the base case simulation. Therefore, the sensitivity of the model behavior to the most uncertain parameters in the model have been investigated. This resulted in *avg. MET value during sport activities* (i.e. physical exertion during sport activities) and the *avg. MET value of NEAT activities* (i.e. physical exertion during daily activities) being the parameters of which the uncertain values exhibit the largest effect on the key performance indicators (KPI). The reason that these parameters have such an effect is 1) because of the large influence of *avg. MET value during NEAT activities* on *avg. energy expenditure on non-exercise related activity*, which is a major determinant of *avg. energy expenditure on exercise related activity* and 2) because the differences in values of the parameter of avg. MET value of sport activity in the uncertainty are relatively large compared to the base case (due to high variance in possible sport intensity).

Subsequently, the robustness of the five policies was tested under these uncertainties and it was shown that the policies *Lifestyle as medicine* and *Eurofit in the neighborhood* seem to be able to reduce the degree of overweight in the population, even under uncertain conditions. Hence, these policies can be considered robust. The reason that these two measures prove effective and the others do not stems from the fact that their effect, through a combined impact on both intake and expenditure, is strong enough to change the direction of the positive energy imbalance occuring in the base case. The measures respond, for example, to *nutritional knowledge* which is an important determinant of food and non-alcoholic drink intake. A combination of the measures '*Lifestyle as medicine*' and '*Eurofit in the neighborhood*' causes a larger reduction than one of these measures individually implemented because the measures both counteract the positive energy imbalance and thus decrease weight gain. One explanation for why the other measures do not work is because they either respond to an aspect in the system that is not as influential in energy imbalance or because they do affect defining aspects, but the effect of these measures on those aspects is not very elevated.

It can be concluded that integrated lifestyle interventions that focus on both energy intake and energy consumption seem best suited to reduce overweight in a neighborhood of the Schildersbuurt and indicate to be robust also in case of the tested possible future circumstances.

6.2 Reflection on the research approach

System Dynamics (SD) was chosen as the modeling technique for this study for a number of reasons. First, SD allowed for continuous simulation of the complex system of overweight on a neighborhood level, characterized by influences of biological, economic, cultural and environmental nature. In addition, SD enabled the possibility to represent the interaction between various system mechanisms and to implement important features of the system such as feedback loops. Also, SD was helpful for the chosen level of aggregation (the neighborhood perspective) and for exploring the long term effect of policy interventions.

Nevertheless, the application of SD for this research question also involves some stumbling blocks. First of all, regarding the level of aggregation. The storage of fat in the body of which an excessive amount leads to overweight happens on an individual level. The responsible mechanism at the physiological level concerns an upset energy balance with a positive value. Two submodels of this study focus on determining the degree of energy imbalance. The third submodel subjects itself to the degree of overweight in the population. Thus, to translate from energy imbalance to the degree of overweight in the population means a conversion from the individual aggregation level to the neighborhood aggregation level. Given the lower aggregation level, it could be considered to apply an agent based model, as this is sufficient in modeling individual agents.

6.3 Limitations of this research

Like most research, this thesis is subject to limitations. the following being the most important to discuss:

- There are limitations with regard to the available literature and data. Obtaining data input for parameters and variables in the model proves difficult because often specific values of neighborhoods are not investigated or because the relationship between factors in the model has not been quantitatively specified before. Therefore, many assumptions had to be made.

For example, it proved difficult to determine the relationship between factors such as financial stress or nutritional knowledge and food intake. These factors have been included in the model but implemented in a simplified way. In addition, the data that is available does not always serve as the best appropriate source. Lifelines (n.d.) data has been used to draw conclusions about determinants on the influence of mental well-being on overweight. However, the interview with Professor J. Seidell revealed that epidemiological data is not the best data to gain knowledge about such relationships. Moreover, correlation between factors in the system is difficult to determine. The exact effect of a determinant is therefore not always observable. An example of this is a possible correlation between socioeconomic status (SES) and ethnicity. In the case of determining the level of sports activity in the neighborhood, a choice had to be made between ethnicity and age as the determining determinant because the available research for data had been framed in this way. This choice was made on the basis of a more pronounced characteristic of the neighborhood, which in the case of the Schildersbuurt is the composition of ethnic groups. Nevertheless, age will also have an effect on sports activity.

- The neighborhood-level overweight system contains a large number of factors from various domains that influence the problem. The study attempted to include the most important determinants and mechanisms in the model to examine the effects of policy interventions and to provide an answer to the research questions. However, given time constraints, it is a condensed version of all the determinants that influence this system. As a result, the policy interventions could not be tested in a specific manner. For example, nutrition is not classified by food products so interventions aimed at eating more fruits and vegetables cannot address these food products in the model. The implementation of such a measure in the model takes place on a variable on a higher aggregation level (the variable *nutritional knowledge*). Other scope limitations refer to certain assumptions made, such as for calculation of resting metabolic rate, where age is involved. A constant average age was assumed, while in neighborhoods with a high number of elderly people a different average rate of metabolism will apply.
- During the model testing phase, historical data about the neighborhood that had not been used in the model was not found, so other components of the model could not be tested for alignment with historical values.
- The model is suitable for the exploration of policy interventions in the Schildersbuurt in The Hague but it cannot be said with certainty whether the model is adequate for policy recommendations for other neighborhoods. Given that, for example, the historical data validation was only conducted with historical data of the Schildersbuurt.

6.4 Scientific contribution of this research

Chapter 1 highlighted that knowledge gaps were found by reviewing the current literature. Although much is known about factors that influence overweight on both the individual as well as neighborhood level, the exact impact of each of these factors in a specific setting is unknown. For several years now, municipalities have been expected to implement local health policies and local policy makers have been responsible for addressing overweight in their neighborhoods. Some measures are known to be effective for some neighborhoods, however, the composition and environment differs greatly from neighborhood to neighborhood, the effect of such a measure in another neighborhood is therefore unknown. There will be variations in the effect of measures given characteristic features of neighborhoods and thus different factors underlying the problem on a local level.

Although system thinking approach studies on overweight at a neighborhood level have been carried out before, these either concern the analysis of populations abroad or do not involve quantitative studies, which means that specific policy recommendations for neighborhoods cannot be made. This study contributed by creating a system dynamics Neighborhood Overweight model that is able to integrate information of existing literature about determinants involved on a neighborhood level in order to be able to generate local policy advice for the Schildersbuurt. It filled the gap between theoretical knowledge and specific practical advice. For this, a lot of assumptions had to be made but they are all based upon extensive study and documented in this thesis.

Also, this research has shown that despite missing data of elements in the model an SD model is suitable to be used as a tool to advise on policy interventions as derived from the model testing phase. In addition, the current study provides quantitative support for the previously found recommendation of Brink et al. (2021) for an integrated approach to overweight at the neighborhood level.

6.5 Societal contribution of this research

The increase in people with excessive weight is of growing concern and is even considered a global epidemic by some scientists. As mentioned above, the causes of overweight and results of policy changes from neighborhood to neighborhood.

This study provides an overview of the most important neighborhood determinants that influence overweight in the population. It also presents a specific understanding of the impact of these determinants in the Schildersbuurt for which the Neighborhood Overweight model is quantified. In addition, this research offers insight into the possible impact of different types of policy measures while considering uncertainties in the model. Therefore, the thesis can be considered as socially relevant as it is able to provide specific policy advice for one neighborhood and at the same time offers a good basis for the exploration of local measures in another neighborhood.

6.6 Recommendations for policy makers

As highlighted in the introduction, an integrated approach of different disciplines is recommended at the local level (Brink et al., 2022). How this is related to the situation in the Schildersbuurt due to specific neighborhood characteristics was previously unclear. The Neighborhood Overweight model was successfully developed, and was able to provide insight of the potential of five different policies. Integrated programs appear to have a beneficial effect to address overweight in the Schildersbuurt. The two policy interventions that emerged from the experiments with the most desirable results are 'Lifestyle as medicine' and 'Eurofit in the neighborhood'. The measure 'Lifestyle as medicine' focuses on stimulating healthy eating and sufficient exercise and has addressed the variables *nutritional knowledge* and *walking time* in the model. The intervention 'Eurofit in the neighborhood' has been implemented to obtain a picture of a similar intervention such as 'Eurofit' or 'Gezond in de buurt in beweging' where nutrition and physical activity are also central, however the focus of physical activity within these projects is more on the daily, non-sporting type of it. A combined approach of both interventions is even more effective. The other three measures applied to the model affect either kcal intake or kcal consumption. They do not appear powerful enough to defeat the positive energy balance so that despite implementation of these measures the degree of overweight among the population continues to grow. The advice for policy makers in the Schildersbuurt is therefore to investigate the possibilities of implementing the integrated measures. The model also contributes to the importance of an integrated approach of domains affecting energy intake and expenditure. Therefore, it is recommended that more of these types of integrated measures focused on these aspects are considered as an option for combating overweight.

6.7 Recommendations for further research

Many assumptions had to be made for the values of input parameters in the model, in order to improve the simulation model it is therefore recommended to collect more neighborhood-specific data and to conduct more research into the (mutual) relationship of factors influencing overweight. In this way, more reliable input values can be implemented in the model. In addition, more subgroups, such as age groups, could be examined as this could potentially affect the level of sports activity and metabolism in neighborhoods. Further development of the simulation model in more detail is also recommended. Specification of components in the model can enable policy interventions to be implemented more specifically (because measures can then respond to more specific parameters they are linked to) allowing further inspection of the effects of policy interventions.

Furthermore, it is recommended to test whether and to what extent the model is able to correspond with real behavior observed in other neighborhoods. On the basis of these findings, the model can be further improved so that it can be deployed as a policy-support tool for other neighborhoods in the Netherlands.

It would also be interesting to combine this SD study with an Agent-based modeling (ABM) approach. The established model required a translation from the individual level to the neighborhood level. As described in the methodology reflection, SD is well suited for the higher aggregation level of the neighborhood, but not for examining the factors influencing a specific individual. ABM can provide support for analyzing individual behavior that occurs at a lower level of aggregation. Such an approach offers perspective given by previous recommendations of Djanatliev and German (2013) for addressing complex problems in the health domain using SD and ABM.

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Appendix A. Elaboration on the scope of the study

A.1 Bulls eye diagram

Factors that fall within the scope of this study can be divided into fully endogenous and partly endogenous variables. Fully endogenous refers to variables calculated by other factors in the model and partly endogenous factors are partly calculated by other factors in the model. Scenarios are factors that affect the system from the outside and which cannot be influenced at the municipal level. Input factors are those factors that the municipality can influence. Finally, there are aspects that are not considered relevant to answering the research question and are therefore kept outside the scope of the research. The bulls eye diagram in Figure 1 provides an overview of the position of factors within this study as well as the domain to which they belong. The different domains and their corresponding factors are highlighted below.

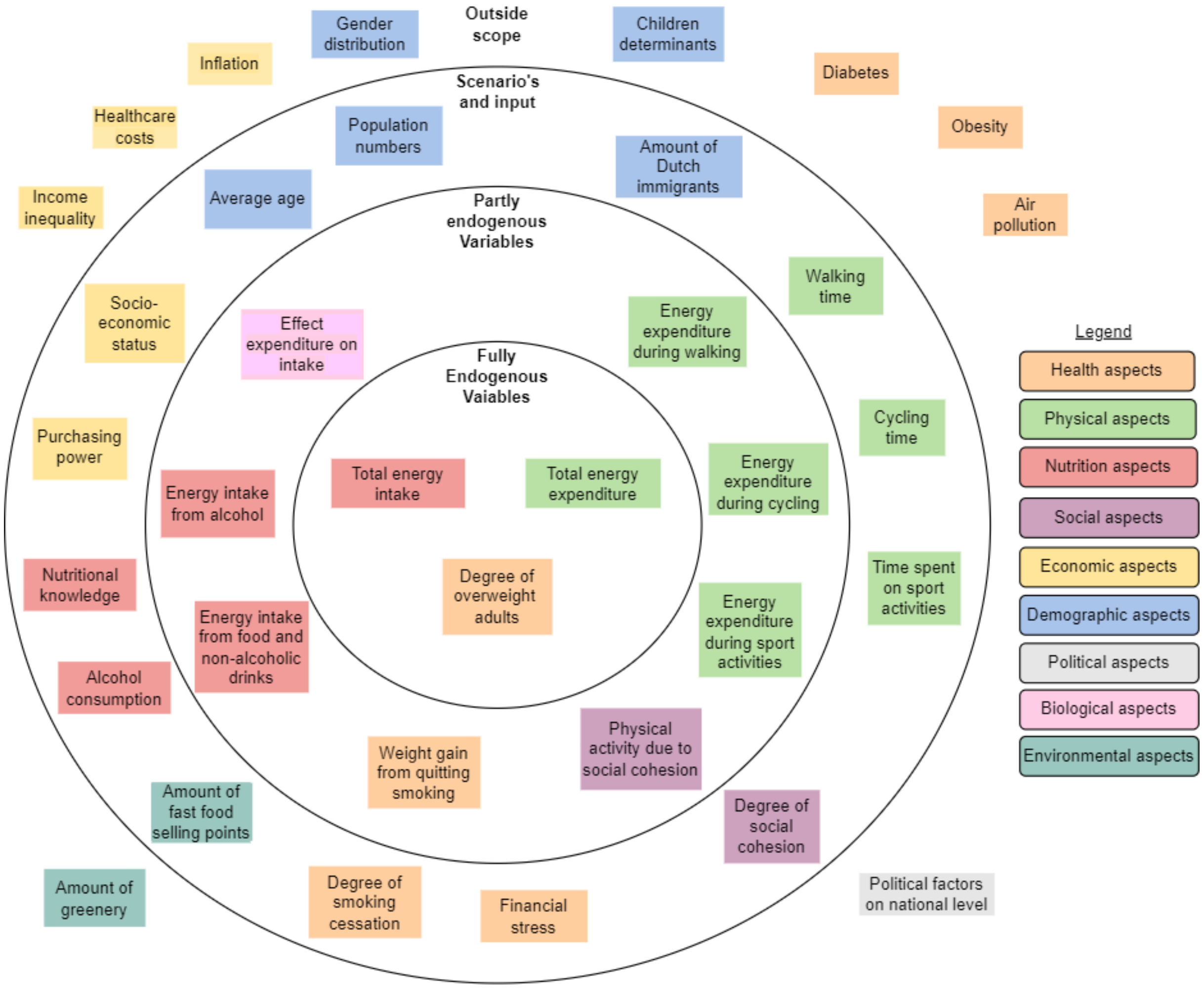


Figure A.1 Bulls eye diagram

Health aspects

The degree of overweight within a neighborhood is an important health aspect that is central to this study. Obesity, which defines a BMI of 30 or higher and is officially considered a disease (WHO, 2000), is outside the scope of this study. The same applies to diabetes, which can arise from being overweight. Other types of health risks caused by, for example, polluted air in a neighborhood are also excluded from the study. In addition, individual health aspects, such as surgical interventions or genetic predisposition, are not examined. Mental health aspects such as financial status are considered in this study given their impact on eating behavior (T. Sluijs, personal communication, December 16, 2021). Smoking cessation is also within the scope of this study as it contributes to weight gain (Filozof et al., 2004).

Physical aspects

Physical activity takes place during different times of the day and ranges from low-intensity daily activities in the household to heavy sports activities. All these aspects are included but not examined in great detail. A distinction is made between 4 levels; walking, cycling, sports activities and other daily activities.

Nutritional aspects

Within the food domain, the intake of food and beverages is the focus. Another aspect within the food domain that affects the intake of food concerns nutritional knowledge which is also in the scope of the model.

Social aspects

Social aspects included in this study are social cohesion and the connection one feels with the neighborhood. The degree to which people are connected has an impact on the time they spend outdoors, which has a positive effect on their movement (Verdonk & van Koperen, 2007).

Economic aspects

People with a low socioeconomic status have fewer resources to adopt a healthy lifestyle (Mackenbach, 2016). Economic aspects at a higher level than the neighborhood level, such as inflation and healthcare costs, are excluded given that they have no neighborhood-specific influence.

Demographic aspects

The demographics in a neighborhood and the ethnicity of the residents also influence factors that play a role in overweight (Nicolaou, Nierkens, & Middelkoop, 2013). However, these variables cannot be influenced by the municipality, which means that they will be considered as a scenario. In demographic terms, this research focuses on the analysis of an unhealthy weight status among adults and determinants affecting children, like healthy food offerings at school, exercise-friendly schoolyards and the number of playgrounds will not be investigated. Differences between gender was not included in the analysis because it is assumed that men and women are equally distributed in the neighborhood.

Political aspects

Finally, there are political aspects that play a role in combating the problem, policy interventions that can be deployed on a local scale are discussed later. Political factors on a national scale, such as national policy towards food and physical activity advertisements are outside the scope of this study. Determinants on a national scale can also have an effect on regional factors which will then be considered.

Biological aspects

Our biological system is focused on keeping body mechanisms in balance, this is the basis of thermogenesis (J. Seidell, personal communication, May 19, 2022). The manner in which consumption affects intake is therefore part of the model.

Environmental aspects

That the environment also influences weight gain has become increasingly clear in recent years, given that the obesogenic environment partly determines our eating behavior (Roy et al., 2015; Mackenbach, 2016; J. Seidell, personal communication, May 19, 2022). The unhealthy suppliers in the neighborhood will therefore be modeled as variables. There may also be a linear relationship between the amount of green space in the neighborhood and the extent to which it encourages people to go outside for physical activity (Gezondheidsraad & RMNO, 2004). However, Den Hertog, Bronkhorst, Moerman, van Wilgenburg (2006) show that there is no evidence for this because of the fact that people in the city are less overweight than people in a village cannot be explained by this. Therefore it was decided to leave this aspect out of the scope of the model.

Recent data will be used to quantify the effects of the variables in the model, with 2015 being the earliest reference year.

Appendix B. Summary of interview

Summary of interview with Prof. Dr. i.r. J. Seidell - Nutrition scientist and university professor at the Vrije Universiteit Amsterdam (May 19, 2022)

Seidell's research group conducts a lot of research in the field of health and overweight, also at the neighborhood level and on the basis of causal loop diagrams. Within this research group the focus is mainly on the food environment and interventions. Sometimes focus groups are used, for example CLDs are established with the inhabitants themselves. This way of working provides the scientists with new insights.

Seidell explains that systems analysis assumes aspects not to be linear. Including the effects of interacting aspects is therefore important. In addition to biological and social factors, environmental factors also have an influence. Often the same determinants influence exercise and food consumption behavior.

He points out that overweight people have a higher resting metabolism. For example, climbing stairs takes much more energy for a heavy person compared to one with less weight. The minutes of activity go down, but the energy expenditure during an activity goes up. If you are carrying 30 kg extra, it takes much more energy to do a certain activity. This also differs per activity, in weight bearing activities such as cycling this plays less of a role than in climbing stairs. Important here is the so-called physical activity level (PAL); the amount of energy you use above your resting metabolism. All activities, whether it's brushing your teeth, running, walking the dog, or sitting, add up to energy expenditure. In fact, the energy balance is naturally regulated, he noticed that this link between expenditure and intake is still missing in the model established so far. There should be another arrow going from weight to resting metabolism.

The best studies concerning energy expenditure are those with doubly labeled water techniques, that is, deuterium and labeled hydrogen (18NH2). If you would look at the doubly labeled water studies where energy consumption is measured per 24 hours, you would see the higher the BMI the higher the 24-hour energy expenditure. And that's partly due to increased resting metabolism and partly due to energy that you consume during exercise because you have to carry more weight. So normally one would say that as people gain weight, their energy expenditure also increases and then they get a new balance. This also applies to energy intake. So, if one consumes 50 kcal a day more than needed, their weight will increase by around half a kilogram and then their energy expenditure will rise again because of their weight gain and they are back in balance. The basis of thermogenesis is the constant establishment of (new) balances. And it is not that if one would eat one more cookie every day that they are 30 pounds heavier over time because your energy expenditure also increases which results in a new equilibrium. So that relationship between expenditure and intake is very important because it provides attenuation of effects. By nature, people keep at the same weight. When you have not eaten for a while, you become less active and vice versa. The primary mechanism in energy balance is balancing the elements of intake and expenditure and the whole human physiology is geared to that. Homeostasis regulation applies to all processes in the body; if something goes wrong there is a mechanism which tries to bring it back in balance.

Seidell indicates that we have created an environment which causes our energy balance to be constantly out of equilibrium. The main aspects he believes play a role in this concern energy density, marketing, price, portion size, convenience, and availability. When food is everywhere available, we as humans tend to eat more. When looking at children they are constantly exposed to unhealthy snacks; there are treats at school, the sports club and at home again. A lot of availability of convenience foods (cheap, high calorie) stimulates energy intake. Total energy consumption depends on frequency times duration times intensity. Intake is determined by how often you eat and the energy content of your food. There is also a theory that states that if food is being poor in certain nutrients (e.g.) protein, you will eat more because your body needs a certain amount of protein. So, it is about more than just calories.

Epidemiological data such as Lifelines do not tell us anything about causality, so these data are not suitable for the purpose of the current study. He explains that financial stress causes one to pay more attention to price. Whereas in case you are short on time you are more inclined to buy convenience foods. Brenner's model, a socio-economic model, describes how human behavior comes about. It shows that behavior is largely determined by individual determinants, such as biology, age and gender. On top of that you have aspects such as social cohesion, income, culture, which in turn are determined by where people live, the environment. Energy-related behavior is determined by micro, macro and meso environmental factors, such as the neighborhood you live in and the family you come from. It involves physical, social and environmental factors and of importance is the interaction between those various factors. So if one has little time, skills and money and is marketed with cheap convenience food that is available everywhere, he/she is very inclined to eat it. It is precisely the interaction of factors that can make someone overweight. And stress, for example, is very difficult to measure, and epidemiological data does not accurately reflect the amount of stress that people experience. There are people who are so stressed that they do not eat anything, but there are also people who start snacking while experiencing stress. It could be that data analysis with epidemiological data will not show a correlation, but on an individual level stress can do a lot, it can decrease or increase energy intake. People can also be in a situation where their attention is mainly focused on short-term thinking, for example if they are worried about whether they will have an income next week. This stress thwarts long-term goals, such as healthy eating and living. A long-term goal such as healthy eating is thwarted by stress.

The problem with epidemiological data is that it is very doubtful whether what people fill in on the questionnaire is actually correct. Especially when it comes to dietary behavior, but also exercise behavior, it is notoriously unreliable. There are many socially desirable answers and sometimes people just do not know it. In addition, the heavier people are, the more they underreport. It has been shown with objectively measured double-mixed water studies that the heavier people are, the higher the energy intake is. With a questionnaire, the higher the weight the lower the energy intake reported. And that leads to such paradoxical cases.

The food consumption survey of the RIVM (the organization of which Seidell is on the supervisory board) is conducted to monitor food intake among Dutch citizens, however with a very limited method. Here the same fundamental problems occur. In fact, these factors should be examined with experimental research. For example, we know that sugary drinks do not have an appetite suppressing effect, so sugar in products is not the only factor that causes excess weight, the form it comes in also makes a difference. If you eat a lot of sugar in solid foods then your appetite still regulates it, but with liquid sugars it does not. So, it is all quite complex.

How many people get heavy in a neighborhood is determined by the environment. And who then becomes heavy is determined by biological factors, such as how sensitive someone is to the environment. It is important to include biological factors in the model as well.

Seidell also indicates that there are large differences in age groups. In addition, what happens in childhood plays a major role. If one is overweight as a child, he/she will also have a greater chance of being overweight later in life. Work also determines the amount of energy one expenses. During heavy physical work a person will burn more energy.

He concludes that the model built so far is a good start. What is important is the behavior and the determinants of the behavior. It is about interaction between different behaviors and also the feedback. He suggests starting by looking at the energy balance again, because expenditure and intake should be connected.

Appendix C. Details of the Vensim model components

This appendix provides a more detailed overview of the built model and input data. It is organized according to the different model components. All variables with associated units, initial values, formulas and sources from which the value or formula was derived are shown in tabular form. In Vensim, subscripts are indicated by brackets [ ]. Sources based on 'own interpretation' denoted by a number are described below the corresponding table.

C.1 Population

Table C1. Variables of the population

Name factor	Unit	Initial Value	Equation	Source
Annual population growth[Ethnic Group]*	1/Year	x	0.0015, 0.0553, -0.0098, -0.0192, -0.0034, 0.026	Alle Cijfers, n.d.
Days per year	Day/Year	x	365	-
Daily population growth	1/Day	x	Annual population growth[Ethnic Group] / Days per year	-
Initial population numbers	Person	x	2710, 2170, 7250, 6390, 8580, 4455	Alle Cijfers, n.d.
Change in population composition[Ethnic Group]	Person/Day	x	Initial population numbers[Ethnic Group] * Daily population growth[Ethnic Group]	Own interpretation [1]
People moving to the neighborhood[Ethnic Group]	Person/Day	x	IF THEN ELSE(Change in population composition[Ethnic Group] > 0 , Change in population composition[Ethnic Group] , 0)	Own interpretation [1]
People moving out of the neighborhood [Ethnic Group]	Person/Day	x	IF THEN ELSE(Change in population composition[Ethnic Group] < 0 , -Change in population composition[Ethnic Group], 0)	Own interpretation [1]
Population[Ethnic Group]	Person	Initial population number[Ethnic Group]	People moving to the neighborhood[Ethnic Group] - People moving out the neighborhood[Ethnic Group]	Own interpretation [1]
Total population	Person		SUM(Population[Ethnic Group!])	Own interpretation [1]

Own interpretation [1]
The populations of the various ethnic groups have gradually increased/ decreased in recent years. Therefore, a fixed daily growth rate has been assumed for each group separately. In case of positive value of growth, people are settling in the neighborhood and in case of negative values, people of this ethnic group are moving away from the neighborhood. This is represented by the IF THEN ELSE functions. The population is determined based on the people moving into the neighborhood minus the people moving out of it. The total population is a sum of the ethnic populations in the neighborhood distinguished in this model.

**The order for the values in the subscripts of the Ethnic Group subgroup is as follows: Dutch, Western, Moroccan, Surinamese/Antillean, Turkish, Other non-western*

C.2 Energy expenditure

Table C2. Variables of the total avg. energy expenditure

Name factor	**Unit**	**Initial Value**	**Equation**	**Source**
Avg. energy expenditure during activity thermogenesis	Kcal/Day	x	Avg. energy expenditure on non-exercise related activity + Avg. energy expenditure on exercise related activity	Levine, 2002
Energy expenditure during rest and activity	Kcal/Day	x	Avg. energy expenditure during activity thermogenesis + Resting metabolic rate	-
Ratio food-induced thermogenesis	Dmnl	x	0.1	Levine, 2002
Total avg. energy expenditure	Kcal/Day	x	Energy expenditure during rest and activity * (1 + Ratio food-induced thermogenesis)	Levine, 2002

Rest metabolic rate

Table C3. Variables of the rest metabolic rate

Name factor	Unit	Initial Value	Equation	Source
Constant in metabolic rate formula	Kcal/Day	x	682.1	Own interpretation (explained in the main body)
Variabel for kcal expense on metabolic rate per kg weight	(Kcal/Day)/Kg	x	11.7	Own interpretation (explained in the main body)
Resting metabolic rate	Kcal/Day	x	Constant in metabolic rate formula + Variabel for kcal expense on metabolic rate per kg weight * Avg. weight in population	Henry, 2005

Exercising energy expenditure

Table C4. Variables of the energy expenditure excluding affected activity level due to weight gain

Name factor	Unit	Initial Value	Equation	Source
Avg. energy expenditure excluding affected activity level due to weight gain	Kcal/Day	x	Additional energy expenditure due to social cohesion + Avg. energy expenditure during sport activity + Avg. energy expenditure with walking and cycling	Own interpretation (explained in main body)

Table C5. Variables of the decrease expense on exercise related activity due to increased weight

Name factor	Unit	Initial Value	Equation	Source
Ratio exercise related activity of total activity	Dmnl	x	1 - Ratio non-exercise related activity of total activity	-
Reduced expense of kcal per decreased number of minutes per day spent on activity	Kcal/(Min/Day)	x	2.38	Johannsen et al., 2008
Reduced expense on exercise related activity due to increased weight	Kcal/Day	x	Decrease in minutes per day spent on activity * Ratio exercise related activity of total activity * Decreased expense in kcal per decreased amount of minutes per day spent on activity	Own interpretation (explained in main body)

Table C6. Variables of the avg. energy expenditure on exercise related activity

Name factor	Unit	Initial Value	Equation	Source
Avg. energy expenditure on exercise related activity	Kcal/Day	x	Avg. energy expenditure excluding affected activity level due to weight gain - Reduced expense on exercise related activity due to increased weight	Own interpretation (explained in main body)

Energy expenditure due to sport activities

Table C7. Variables of the energy expenditure due to sport activities

Name factor	Unit	Initial Value	Equation	Source
Avg. hours per week of sport activities[Ethnic Group]	Hour/Week	x	1.03, 1.03, 0.99, 1.05, 0.83, 0.96	Cornelisse-Vermaat & Van Den Brink, 2007)
Minutes per hour	Min/Hour	x	60	-
Avg. time spent on sport activities per week	Min/Week	x	((SUM(Avg. hours per week of sport activities[Ethnic Group!] * Population[Ethnic Group!])) * Minutes per hour) / SUM(Population[Ethnic Group!])	Own interpretation [2]
Avg. MET value of sport activities	Kcal/Kg/Min	x	6.8	Assumption based on Jetté et al., 1990; Mendes et al., 2018
Oxygen consumption per MET unit	Ml/Kg/Min	x	3.5	Jetté, Sidney, & Blümchen, 1990; Morris et al., 1993
Oxygen consumption	Ml/Kg/Min	x	Oxygen consumption per MET unit * Avg. MET value of sport activities	Jetté et al., 1990; Morris et al., 1993
Constant in MET formula	Ml/Kcal	x	200	Voedingscentrum, n.d.
Energy consumption per minute of sport activity	Kcal/Min	x	Oxygen consumption* Avg. weight in population / Constant in MET formula	Voedingscentrum, n.d.
Avg. energy consumption during sport activity	Kcal/Day	x	(Avg. time spent on sport activities per week * Energy consumption per minute of sport activity) / Days per week	-

Own interpretation [2]
The average sport activity of persons in a neighborhood is calculated by multiplying the sport activity of people of a certain ethnic group by the number of people of that ethnic group living in that neighborhood divided by the total number of people living in that neighborhood.

Energy expenditure due to biking and walking

Table C8. Variables of the energy expenditure with walking and cycling

Name factor	**Unit**	**Initial Value**	**Equation**	**Source**
Walking time[Ethnic Group]	Min/Week	x	64,66,58,58,58,58	Gao et al., 2017
Avg. walking time	Min/Week	x	SUM(Walking time[Ethnic Group!] * Population[Ethnic Group!]) / SUM(Population[Ethnic Group!])	Own interpretation (similar to formula of avg. time spent on sport activities per week)
Energy expenditure per minute walking	Kcal/Kg/Min	x	0.07	Langford et al., 2017
Days per week	Day/Week	x	7	-
Avg. energy expenditure with walking	Kcal/Day	x	("Avg. walking time"*"Avg. weight in population"*Energy expenditure per minute walking)/Days per week	Gao et al., 2017; Langford et al., 2017
Cycling time[Ethnic Group]	Min/Week	x	78,70,52,52,52,52	Gao et al., 2017
Avg. cycling time	Min/Week	x	SUM(Cycling time[Ethnic Group!] * Population[Ethnic Group!]) / SUM(Population[Ethnic Group!])	Own interpretation (similar to formula of avg. time spent on sport activities per week)
Energy expenditure per minute cycling	Kcal/Kg/Min	x	0.09	Langford et al., 2017
Avg. energy expenditure with cycling	Kcal/Day		("Avg. cycling time"*"Avg. weight in population"*Energy expenditure per minute cycling)/Days per week	Gao et al., 2017; Langford et al., 2017
Avg. energy expenditure with walking and cycling	Kcal/Day		Avg. energy expenditure with cycling + Avg. energy expenditure with walking	-

Energy expenditure due affected by social cohesion

Table C9. Variables of energy expenditure due to social cohesion

Name factor	Unit	Initial Value	Equation	Source
Avg. degree of social cohesion	Dmnl	x	5.60	Gemeente Den Haag, n.d.
Degree of social cohesion in neighborhood	Dmnl	x	5.43	Gemeente Den Haag, n.d.
Difference between social cohesion average and neighborhood	Dmnl	x	Degree of social cohesion in neighborhood - Avg. degree of social cohesion	-
Energy expenditure per minute of low physical activity per kg	Kcal/Kg/Min	x	0.0876	Mackenbach, 2016
Energy expenditure per minute of low physical activity	Kcal/Min	x	Dutch avg. weight * Energy expenditure per kg per minute of low physical activity	Own interpretation
Lookup additional physical activity	Min/Day	x	WITH LOOKUP(Difference between social cohesion average and neighborhood ([(0,0)-(10,10)],(-7.99876,-2.9802),(-6.73704,-2.97867),(-4.83878,-2.97867),(-4.19087,-2.96445),(-2.07664,-2.9218),(-1.43621,-2.78666),(-0.968438,-2.30925),(-0.768041,-1.64987),(-0.510258,-0.575597),(-0.17225,-0.135963),(0,0),(0.304868,0.0689655),(0.743784,0.412322),(1.28966,1.59777),(1.65259,2.23223),(2.2002,2.65877),(2.95754,2.81517),(4.27414,2.90047),(7.25688,2.92891),(9.99495,2.94313))	Own interpretation [3]
Additional	Kcal/Day	x	Lookup additional physical activity *	Own

energy expenditure due to social cohesion			Energy expenditure per minute of low physical activity	interpretation

<u>Own interpretation [3]</u>

Mackenbach (2016) conducted research on the influence of network size on physical activity levels. She found that with an increase of one new person to network size, physical activity in women increased by 9.3 minutes while in men it decreased by 4.1 minutes. On average, this would mean an increase by 2.6 minutes per new member. However, this seems quite high, therefore lower values were assumed for the lookup function. For the lookup function, it is assumed that the larger a difference with the reference value initially leads to an increasingly larger difference with the decrease in physical activity. However, the growth of this decrease becomes smaller and smaller because an even larger difference in social cohesion will no longer affect activity at some point, is the expectation.

Non-exercising energy expenditure

There is a wide variation in the number of minutes a healthy person spends in activity reported by researchers (Johannsen et al., 2008; Davis et al., 2006). Based on the aforementioned studies, the number of minutes per day of activity was assumed to be 350 for this report. The difference in weight between a person of healthy weight and the average weight of a person in the neighborhood times the decrease in minutes per day spent on activity per kg increase in weight gives the number of minutes a person in the neighborhood spends less than average on activity. Subtracting these reduced minutes from the 350 minutes spent on activity by a person of healthy weight gives the initial value of the number of minutes spent on activity by a person in the neighborhood (see Figure C.1).

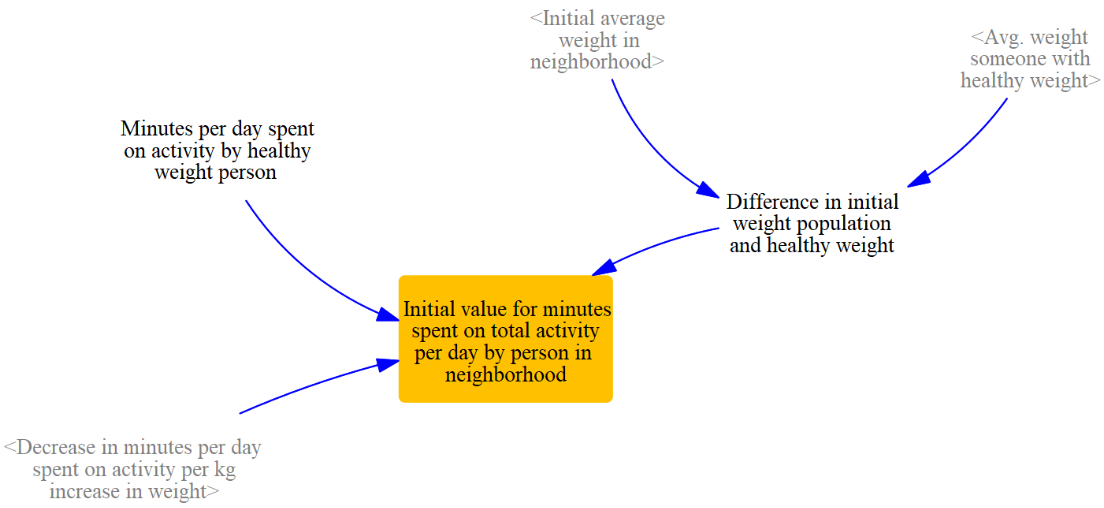


Figure C.1. Initial value for minutes spent on total activity per day by person in neighborhood

Table C10. Variables of value for minutes spent on total activity per day by person in neighborhood

Name factor	**Unit**	**Initial Value**	**Equation**	**Source**
Minutes per day spent on activity by healthy	Min/Day	x	350	Assumption based on Davis et al., 2006; Johannsen et al., 2008

weight person				
Difference in initial weight population and healthy weight	Kg	x	Initial average weight in neighborhood - Avg. weight someone with healthy weight	-
Initial value for minutes spent on total activity per day by person in neighborhoo d	Min/Day	x	Minutes per day spent on activity by healthy weight person - Difference in initial weight population and healthy weight * Constant of decrease in minutes per day spend on activity per kg increase in weight	-

Table C11 Variables of minutes spent on non-exercising activity per day by person in neighborhood

Name factor	Unit	Initial Value	Equation	Source
Ratio non-exercise related activity of total activity	Dmnl	x	0.7	Assumption based on Levine, 2002; Von Loeffelholz & Birkenfeld, 2018
Initial value for minutes spent on non-exercising activity per day by person in neighborhood	Min/Day	x	Initial value for minutes spent on total activity per day by person in neighborhood * Ratio of non-exercise related activity of total activity	-
Decrease in minutes per day spent on activity per kg increase in weight	Min/Day/Kg	x	5.6	Own interpretation [4]
Decrease in minutes per day spent on activity	Min/(Day*Day)	x	Constant of decrease in minutes per day spent on activity per kg increase in weight * added weight per day	-
Decrease in minutes per day of non-exercising activity	Min/(Day*Day)		Decrease in minutes per day spent on activity * Ratio of non-exercise related activity of total activity"	-

Own interpretation [4]

The decrease in minutes per day spent in activity per kg of weight gain was calculated using research by Donahoo et al. (2004). This study addressed the time spent in activity between people with different BMI. It is assumed that the average height is 1.741 meters (CBS, 2019). Thus, the average weight can be calculated. The ratio of the difference in weight to the difference in minutes spent in activity gives the decrease in minutes per day spent in activity per kg increase in weight.

Table C12. Variables of avg. energy expenditure on non-exercise related activity

Name factor	Unit	Initial Value	Equation	Source
Avg. MET value during NEAT activities	Dmnl	x	0.8	Assumption based on Holtermann & Stamatakis, 2019 + BRON
Oxygen consumption during NEAT activities	Ml/(Min*Kg)	x	Avg. MET value during NEAT activities * Oxygen consumption per MET unit	Voedingscentrum, n.d.
Avg. energy expenditure per minute of NEAT activities per kg	Kcal/(Kg*Min)	x	Oxygen consumption during NEAT activities/Constant in MET formula	Voedingscentrum, n.d.
Avg. energy expenditure during non-exercise related activity per kg	Kcal/Kg/Day	x	Minutes spent on non-exercising activity per day by person in neighborhood * Avg. energy expenditure per minute of NEAT activities per kg	Voedingscentrum, n.d.
Avg. energy expenditure on non-exercise related activity	Kcal/Day	x	Avg. energy expenditure during non-exercise related activity per kg * Avg. weight in population"	Voedingscentrum, n.d.

C.3 Energy intake

Table C13. Variables of avg. daily energy intake from food and non-alcoholic drinks

Name factor	Unit	Initial Value	Equation	Source
Avg. daily energy intake in neighborhood	Kcal/Day	x	Avg. kcal intake due to alcohol consumption + Avg. daily energy intake from food and non-alcoholic drinks + Extra kcal consumed due to ultra-processed diet on average	Own interpretation (explained in main body)

Kcal intake from food and non-alcoholic drinks

Table C14. Variables of daily energy intake determined by nutritional value corrected for underreporting per group

Name factor	Unit	Initial Value	Equation	Source
Level of education[Level of education groups]**	Dmnl	x	0.548, 0.319, 0,133	Gemeente Den Haag, n.d.
Grams intake proteins per population group[Level of education groups]	Gram/Day	x	81.8, 83.7, 85.6	Van Rossum et al., 2020
Calories per gram of protein	Kcal/Gram	x	4	Voedingscentrum, n.d.
Proteins[Level of education groups]	Kcal/Day	x	(Level of education[Level of education groups] * Grams intake proteins per population group[Level of education groups] * Calories per gram of protein) / Level of education[Level of education groups]	Van Rossum et al., 2020 + Voedingscentrum, n.d.
Grams intake fat per population group[Level of education groups]	Gram/Day	x	86, 88, 90	Van Rossum et al., 2020
Calories per gram of fat	Kcal/Gram	x	9	Voedingscentrum, n.d.
Fats[Level of education groups]	Kcal/Day	x	(Level of education[Level of education groups] * Grams intake fat per population group[Level of education groups] * Calories per gram of fat) / Level of education[Level of education groups]	Van Rossum et al., 2020 + Voedingscentrum, n.d.
Grams intake carbs per population group[Level of education groups]	Gram/Day	x	228, 243, 238	Van Rossum et al., 2020
Calories per gram of carb	Kcal/Gram	x	4	Voedingscentrum, n.d.

Carbs[Level of education groups]	Kcal/Day	x	(Level of education[Level of education groups] * Grams intake carbs per population group[Level of education groups] * Calories per gram of carb) / Level of education[Level of education groups]	Van Rossum et al., 2020 + Voedingscentrum, n.d.
Grams intake fibers per population group[Level of education]	Gram/Day	x	19.2, 20.2, 22.2	Van Rossum et al., 2020
Calories per gram of fiber	Kcal/Gram	x	2	Voedingscentrum, n.d.
Fibers[Level of education groups]	Kcal/Day	x	(Level of education[Level of education groups] * Grams intake fibers per population group[Level of education groups] * Calories per gram of fiber) / Level of education[Level of education groups]	Van Rossum et al., 2020 + Voedingscentrum, n.d.
Daily energy intake determined by nutritional value per group[Level of education groups]	Kcal/Day	x	Carbs[Level of education groups]+Fats[Level of education groups]+Proteins[Level of education groups]+Fibers[Level of education groups]	Van Rossum et al., 2020
Degree of underreporting in food consumption survey[Level of education groups]	Dmnl	x	0.03, 0.03, 0.03	Assumption based on Prof. J. Seidell (personal communication, May 19, 2022)
Daily energy intake determined by nutritional value corrected for underreporting per group[Level of education groups]	Kcal/Day	x	Daily energy intake determined by nutritional value per group[Level of education groups] * (1+Degree of underreporting in food consumption survey [Level of education groups])	-

***The order for the values in the subscripts of the Level of education subgroups is as follows: Low, Medium, High*

Table C15. Variables of avg. daily energy intake from food and non-alcoholic drinks

Name factor	**Unit**	**Initial Value**	**Equation**	**Source**
Purchasing power[Level of education groups]	Dmnl	x	1, 1, 1	Own interpretation [5]
Financial stress[Level of education groups]	Dmnl	x	1, 1, 1	Own interpretation [5]
Nutritional knowledge[Level of education groups]	Dmnl	x	1, 1, 1	Own interpretation [5]

<u>Own interpretation [5]</u>
Given the absence of data on the relationships of these variables with intake, this setup of the variables in the model was chosen.

Kcal intake due to alcohol consumption

To estimate alcohol consumption, a number of variables are needed. These are shown in figure xx.

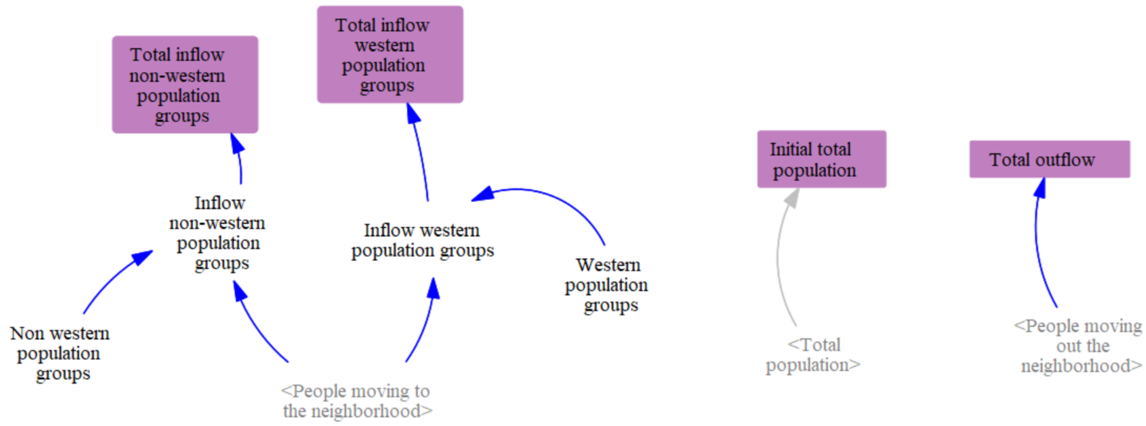


Figure C.2. Variables for calculating alcohol consumption

There are significant differences in alcohol consumption between people with a Dutch and migrant background (Trimbos, 2022). In the model, Western and Dutch population groups are assigned to the first group, and the Turkish, Moroccan, Surinamese/Antillean and other non-Western groups to the second group, respectively.

Table C16. Variables for calculating alcohol consumption

Name factor	Unit	Initial Value	Equation	Source
Non-western population group[Ethnic Group]	Dmnl	x	0, 0, 1, 1, 1, 1	Own interpretation [6]
Inflow non-western population groups[Ethnic Group]	Person/Day	x	People moving to the neighborhood[Ethnic Group] * Non western population groups[Ethnic Group]	Own interpretation [6]
Total inflow non-western population groups	Person/Day	x	SUM(Inflow non-western population groups[Ethnic Group!])	Own interpretation [6]
Western population groups[Ethnic Group]	Dmnl	x	1, 1, 0, 0, 0, 0	Own interpretation [6]
Inflow western population groups[Ethnic Group]	Person/Day	x	People moving to the neighborhood[Ethnic Group] * Western population groups[Ethnic Group]	Own interpretation [6]
Total inflow western population groups	Person/Day	x	SUM(Inflow western population groups[Ethnic Group!])	Own interpretation [6]
Initial total population	Person	x	INITIAL(Total population)	-
Total outflow	Person/Day	x	SUM(People moving out the neighborhood[Ethnic Group!])	-

<u>Own interpretation [6]</u>
The subscripts of the population parameter consists of the order: Dutch, Western, Moroccan, Surinamese/Antillean, Turkish, Other Non-Western. The same order is maintained in the inflow of Western and Non-Western populations which explains the position figure 1 in these formulas (since the Dutch and Western populations are considered western and the others are considered Non-Western).

Figure C.3 provides a representation of the variables involved in the trend of drinking less alcohol.

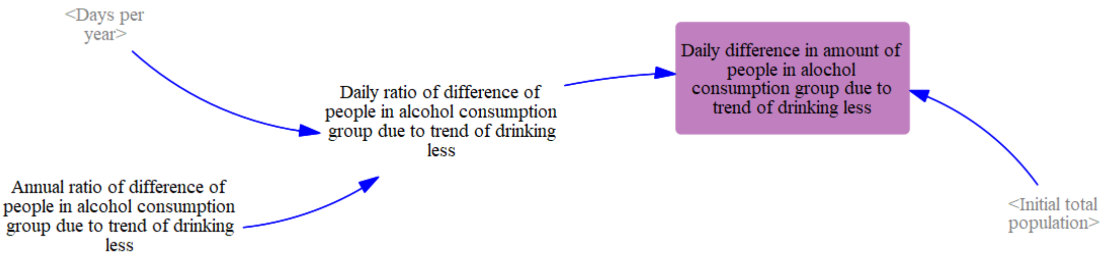


Figure C.3. Variables of daily difference of people in alcohol groups due to trend of drinking less

Table C17. Variables of daily difference of people in alcohol groups due to trend of drinking less

Name factor	Unit	Initial Value	Equation	Source
Annual ratio of difference of people in alcohol consumption group due to trend of drinking less[Alcohol user groups]	1/Year	x	0.026, 0, -0.026, 0, 0	Own interpretation [7]
Daily ratio of difference of people in alcohol consumption group due to trend of drinking less[Alcohol user groups]	1/Day	x	Annual ratio of difference of people in alcohol consumption group due to trend of drinking less[Alcohol user groups] / Days per year	-
Daily difference in amount of people in alcohol consumption group due to trend of drinking less	Person/Day	x	Daily ratio of difference of people in alcohol consumption group due to trend of drinking less[Alcohol user groups] * Initial total population	-

<u>Own interpretation [7]</u>
The national ratio of people across alcohol consumption groups for 2015 and 2020 are available from Trimbos (n.d.). Using these numbers, the difference between the years was calculated and also corrected for population growth retrieved from the CBS (n.d.).

Table C18. Variables of distribution of population over alcohol consumption groups

Name factor	Unit	Initial Value	Equation	Source
Difference due to drinking less[Alcohol user groups]	Person/Day	x	IF THEN ELSE(Time <=2000 , Daily difference of people in alcohol groups due to trend of drinking less[Alcohol user groups], 0)	Own interpretation [8]
Ratio initial distribution of people over alcohol groups[Alcohol user groups]	Dmnl	x	0.47, 0.40, 0.06, 0.04, 0.03	Karamali et al., 2014
Initial distribution of people over alcohol groups[Alcohol user groups]	Person	x	Initial distribution of people over alcohol groups[Alcohol user groups] * Initial total population	Own interpretation [8]
Difference due to people leaving the neighborhood	Person/Day	x	Initial distribution of people over alcohol groups[Alcohol user groups] * Total outflow	Own interpretation [8]
Probability of western being in a specific group[Alcohol user groups]	Dmnl	x	0.17, 0.66, 0.08, 0.045, 0.045	RIVM, 2020; Trimbos 2022
Difference due to people entering the neighborhood (non-western)	Person/Day	x	Probability of western being in a specific group[Alcohol user groups] * "Total inflow non-western population groups"	Own interpretation [8]
Probability of non-western being in a specific group[Alcohol user groups]	Dmnl	x	0.35, 0.52, 0.06, 0.035, 0.035	RIVM, 2020; Trimbos 2022
Difference due to people entering the	Person/Day	x	"Probability of non-western being in a specific group"[Alcohol user groups] * Total inflow western population groups	Own interpretation [8]

neighborhood(western)				
Distribution of population over alcohol consumption groups	Person	Initial distribution of people over alcohol groups[Alcohol user groups]	Difference due to people entering the neighborhood (western)[Alcohol user groups] + Difference due to people entering the neighborhood (non-western)[Alcohol user groups] - Difference due to drinking less[Alcohol user groups] - Difference due to people leaving the neighborhood[Alcohol user groups]	Own interpretation [8]

Own interpretation [8]

A health survey was conducted in the Schilderswijk in 2012 for which a report with the outcomes has been prepared (Karamali et al., 2014). The distribution of people over alcohol consumption groups retrieved from this survey was submitted as the initial value for the distribution after which the model was simulated for 3 years to obtain the initial values of 2015 (starting point of the simulation of this model).

In this model, it is assumed that the distribution of people among the alcohol groups depends on the people moving to and from the neighborhood. Here a distinction is made between different ethnic groups as differences are found in consumption of alcohol between people of a certain origin (Trimbos, 2022). Therefore, a probability of someone moving to / from the neighborhood to belong to a certain alcohol consumption group has been included. In addition, there is also a trend observed of drinking less alcohol over the last few years until 2020 (RIVM, 2020) which also affects the distribution of people across the alcohol groups.

Table C19. Variables of avg. kcal intake due to alcohol consumption

Name factor	**Unit**	**Initial Value**	**Equation**	**Source**
Extra daily kcal per group of alcohol user	Kcal/Day	x	0, 0, 175, 210, 210	Own interpretation [9]
Alcohol consumption per alcohol group	Person*(Kcal/Day)	x	Extra daily kcal per group of alcohol user[Alcohol user groups] * Distribution of population over alcohol consumption groups[Alcohol user groups]	-
Total alcohol consumption	Person*(Kcal/Day)	x	SUM(Alcohol consumption per alcohol group[Alcohol user groups!])	-
Avg. kcal intake due to alcohol consumption	Kcal/Day	x	Total alcohol consumption/Total population	-

Own interpretation [9]

Based on the reports of Trimbos (2022) and (Karamali et al., 2014), the model distinguished between 5 groups of alcohol consumers. Karamali, Berns, van Dijk & van der Meer (2014) define excessive drinking as drinking more than 21 glasses per week for men and more than 14 glasses per week for women. On average, this equates to drinking at least 17.5 glasses per week and which would mean an average of 2.5 per day. Heavy drinkers are men who consume more than 6 glasses of alcohol at least one day a week and women who consume more than 4 glasses of alcohol at least one day a week. For the group of heavy drinkers it is assumed that they drink on average 3 glasses per day. Problem drinkers have the same drinking behavior as heavy drinkers only they experience other mental and physical problems (Karamali, Berns, van Dijk & van der Meer, 2014), for them an average of 3 glasses per day is assumed.

A standard glass of alcohol contains around 70 kcal (Trimbos, n.d.). On top of this comes the kcal intake as a result of the composition of the drink and the amount of sugars. Since people who consume a glass of alcohol may do so in replacement of a non-alcoholic sugary drink, this model assumes 70 kcal extra intake per glass of alcohol. This brings the kcal consumed per day by an excessive drinker to 175 kcal and that of a heavy and problematic drinker to 210 kcal. Obviously no extra kcal have been calculated for non-drinkers, this also applies to the group that drinks occasionally because it is assumed that their drinking behavior has no significant influence on their kcal intake.

Kcal consumed due to ultra-processed diet

Table C20. Variables of percentage of people having an ultra-processed diet

Name factor	Unit	Initial Value	Equation	Source
Initial amount of food suppliers	Supplier	x	28	Pointer (KRO-NCRV), 2021
Annual increase of unhealthy food suppliers	Supplier/Year	x	0.5	Pointer (KRO-NCRV), 2021
Daily increase of unhealthy food suppliers	Supplier/Day	x	Annual increase of unhealthy food suppliers / Days per year	-
Amount of food suppliers	Supplier	Initial amount of food suppliers	Daily increase of unhealthy food suppliers	-
10.000	Person	x	10000	-
Population divided by 10.000	Dmnl	x	Total population / 10.000	-
Unhealthy	Supplier	x	Amount of food suppliers / Population	-

food suppliers per 10.000 citizens			divided by 10.000	
Unhealthy food supplier per person	Supplier/Person	x	Unhealthy food suppliers per 10.000 citizens / 10.000"	-
Lookup percentage of people having an ultra-Processed diet	Dmnl	x	([(0,0)-(10,10)], (0,0.045),(0.0006,0.051),(0.0008,0.055),(0.0009,0.063),(0.001,0.075),(0.0011,0.089),(0.0015,0.14),(0.002,0.18),(0.003,0.22),(0.005,0.25),(0.01,0.3),(0.05,0.45),(0.1,0.58),(0.25,0.7),(1,0.8))	Assumption based on Mackenbach, 2016
Ratio of people having an ultra-processed diet	Dmnl	x	"Lookup percentage of people having an ultra-processed diet"	-

Table C21. Variables of extra kcal consumed due to ultra-processed diet on average

Name factor	**Units**	**Initial Value**	**Equation**	**Source**
Dutch avg. ratio of people having an ultra-processed diet	Dmnl	x	0.025	Assumption based on Mackenbach, 2016
Difference in ratio of people having an ultra-processed diet in the neighborhood compared to the average	Dmnl	x	Ratio of people having an ultra-processed Diet - Dutch avg. ratio of people having an Ultra-Processed Diet	-
Extra kcal with ultra-processed diet	Kcal/Day	x	500	Hall et al., 2019
Extra kcal consumed due to ultra-	Kcal*Person/Day	x	Difference in percentage of people having an ultra-processed diet in the neighborhood compared to the average	-

processed diet			* Total population * Extra kcal with ultra-processed diet	
Extra kcal consumed due to ultra-processed diet on average	Kcal/Day	x	Extra kcal consumed due to ultra-processed diet / Total population	-

C.4 Effect of energy expenditure on food intake

Table C22. Variables of otal avg. energy intake

Name factor	**Units**	**Initial Value**	**Equation**	**Source**
Difference expenditure and intake	Kcal/Day	x	Total avg. energy expenditure - Avg. daily energy intake in neighborhood	-
Delay time adjusted leptin levels in weeks	Week	x	12	Bouassida et al., 2006
Delay time adjusted leptin levels in days	Day	x	Delay time adjusted leptin levels in weeks * Days per week	-
Ratio physiologicall y determined intake	Dmnl	x	0.5	Westerterp-Plantenga, 2001
Physiologicall y determined intake	Kcal/Day	x	Difference expenditure and intake * Ratio physiologically determined intake	-
Avg. daily physiologicall y determined intake	Kcal/Day		DELAY3(Physiologically determined intake, Delay time adjusted leptin levels in days)	Bouassida et al., 2006
Total avg. energy intake	Kcal/Day	x	Avg. daily cognitive determined energy intake + Avg. daily physiologically determined intake	Westerterp-Plantenga, 2001

C.5 Effect of smoking cessation on weight gain

Table C23. Variables of effect of smoking cessation on weight gain

Name factor	**Unit**	**Initial Value**	**Equation**	**Source**

Ratio of people in neighborhood smoking over time	1/Day	x	WITH LOOKUP (Time) Lookup ([(0,0)-(10,10)], (0,0.304),(344.983,0.299661),(730,0.285),(1095,0.268),(1460,0.251),(1825,0.234),(3000,0.19),(4000,0.17),(9125,0.15))	Assumption based on Gemeente Den Haag, n.d.; RIVM, n.d.
New smokers	Person/Day	x	Sum of people moving to the neighborhood * Ratio of people smoking	Own interpretation (explained in main body)
Initial ratio of smokers in neighborhood	Dmnl	x	0.304	Assumption based on Gemeente Den Haag, n.d.
Percentage of people smoking	Dmnl	x	Smokers in neighborhood / Total population * 100	-
Smoking cessation	Person/Day	x	WITH LOOKUP(Time) Lookup ([(0,0)-(10,10)], (0,0.1729),(1,0.1729),(507.99,0.846591),(959.536,1.3125),(1091.24,1.41477),(1335.82,1.46591),(1599.23,1.40341),(1712.11,1.30114),(1937.89,1.0625),(2163.66,0.823864),(2596.39,0.511364),(3273.71,0.3863),(5117.53,0.3863),(9125,0.3863))	Assumption based on Gemeente Den Haag, n.d.; RIVM, n.d.
Smokers in neighborhood	Person	Total population * Initial ratio of smokers in neighborhood	New smokers - Smoking cessation	-
Total weight gain per smoker that quits	Kg	x	4.5	Audrain-McGovern & Benowitz, 2011
Total weight gain of smokers that quit	Person*Kg/Day	x	Smoking cessation * Total weight gain per smoker that quits	-
Delay time weight gain smoking cessation	Day	x	100	Own interpretation [9]
Total weight gain of	Person*Kg/Day	x	DELAY3(Total weight gain of smokers that quit, Delay time weight gain	Own interpretation [9]

smokers that quit over time			smoking cessation)	
Avg. daily weight gain due to smoking cessation	Kg/Day	x	Avg. daily weight gain per smoker that quits / Total population	Own interpretation [9]

<u>Own interpretation [9]</u>

Based on the percentage of smokers in the schilderswijk in 2012 and 2016, the proportion of smokers for 2015, *initial ratio of smokers in the neighborhood*, was determined. The assumption is that between 2012 and 2016 the number of smokers decreases each year by the same unit. The lookups for smoking cessation and ratio of people smoking were created using the data that is available. The function for the lookups continues for 20 years (until day 9125) because data is available from them (RIVM, n.d.). A third-order delay was chosen because weight gain occurs primarily in the first few months (Audrain-McGovern & Benowitz, 2011; Filozof et al., 2004) and the center of gravity of a third-order delay is consistent with this. A value of 100 days for the delay time corresponded best with a third order delay of 1 year. The total weight gain of smokers is divided by the total population so that the average weight gain of individuals in the neighborhood can be determined.

C.6 Degree of overweight in the population

Table C24. Variables of avg. daily energy weight gain in population

Name factor	Unit	Initial Value	Equation	Source
Energy imbalance	Kcal/Day	x	Total avg. energy intake - Total avg. energy expenditure"	Ravussin & Bogardus, 2000
Annual weight gain per daily kcal energy imbalance	(Kg/Year) / (Kcal/Day)	x	0.05	Hall et al., 2011
Daily weight gain per daily kcal energy imbalance	(Kg/Day) / (Kcal/Day)	x	Annual weight gain per daily kcal energy imbalance / Days per year	-
Avg. daily weight gain in population	Kg/Day	x	Energy imbalance * Daily weight gain per daily kcal energy imbalance + Avg. daily weight gain due to smoking cessation	-

Table C25. Variables of avg. weight gain in population

Name factor	Unit	Initial Value	Equation	Source

Delay time on weight gain	Day	x	125	Hall et al., 2011
Initial value added weight	Kg/Day	x	0.00057	Own interpretation [10]
Added weight per day	Kg/Day	x	DELAY3I(Avg. daily weight gain in population, Delay time on weight gain, Initial value added weight)	Own interpretation [10]
Avg. weight someone with overweight	Kg	x	84.9	Own interpretation [11]
Avg. weight someone with overweight	Kg	x	69.7	Own interpretation [11]
Initial average weight in neighborhoo d	Kg	x	Avg. weight someone with healthy weight * (1-Initial ratio people with overweight) + Avg. weight someone with overweight * Initial ratio people with overweight	-
Avg. weight in population	Kg	Initial average weight in neighborhood	Added weight per day	-

<u>Own interpretation [10]</u>

Weight gain due to energy imbalance has a delay. A 3rd order delay was chosen because the weight gain is gradual. As the variable added weight per day occurs in a feedback loop, it is necessary to add an initial value to the formula of this parameter. So that a variable in the model calculated from the variable added weight per day has a starting value designated. The initial value of added weight per day is chosen in line with the course of the added weight per day graph.

<u>Own interpretation [11]</u>

Based on length and BMI, weight can be calculated as follows;

$$Weight = BMI * length^2$$

$$where\ weight\ in\ kg, BMI\ in\ kg/m^2\ and\ length\ in\ M$$

The calculations of the averages for a healthy weight and an overweight person are based on assumptions of having a BMI of 23 and 28 kg/m^2 respectively. The BMI of 23 was chosen because it was the average among lean people in the study by Johansson, Welk, Sharp, & Flakoll (2008). The BMI of 28kg/m^2 is considered appropriate because it is between the minimum value of the BMI of being overweight (25 kg/m^2) and the starting value of BMI of obesity (30 kg/m^2). The average height of Dutch people is 1.741 meters and has remained nearly constant in recent years (CBS, 2019).

Table C26. Variables of ratio increase of overweight population per day

Name factor	Unit	Initial Value	Equation	Source
Annual ratio increase in overweight population per kg annual weight gain	1/Kg	x	0.0199	Own interpretation (explained in main body)
Daily ratio increase in overweight population per kg daily weight gain	1/Kg	x	Annual ratio increase in overweight population per kg annual weight gain	-
Ratio increase of overweight population per day	1/Day	x	Added weight per day * Daily ratio increase in overweight population per kg daily weight gain	-

Table C27. Variables of people with overweight

Name factor	Unit	Initial Value	Equation	Source
Initial ratio people with overweight in neighborhood	Dmnl	x	0.5775	W. Van Bijsterveld, personal communication, July 22, 2022
Initial amount of people with overweight	Person	x	Initial ratio people with overweight in neighborhood * Total population	-
Sum of people moving to the district	Person/Day	x	SUM(Change in population composition[Ethnic Group!])	Own interpretation [12]
People with healthy weight moving to the neighborhood	Person/Day	x	Sum of people moving to the district * (1-Initial ratio people with overweight in neighborhood)	-
People with overweight moving to neighborhood	Person/Day	x	Sum of people moving to the district * Initial ratio people with overweight in neighborhood	-
Inflow overweight people	Person/Day	x	Ratio increase of overweight population per day*People with healthy weight	-

People with healthy weight	Person	Total population - Initial amount of people with overweight	People with healthy weight moving to the neighborhood - Inflow overweight people	-
People with overweight	Person	Initial amount of people with overweight	Inflow overweight people + People with overweight moving to neighborhood	-

<u>Own interpretation [12]</u>
Since the population numbers were measured in subscripts of different ethnicities, a sum function is used to calculate the total number of people moving to the district (in case of a positive value).

Table C28. Variables of percentage people with overweight in neighborhood

Name factor	**Unit**	**Initial Value**	**Equation**	**Source**
Percentage people with overweight in neighborhoo d	Dmnl	x	(People with overweight/Total population)*100	-
Ratio increase people with overweight	Dml	x	(Percentage people with overweight in neighborhood / 100 - Initial ratio people with overweight in neighborhood) / Initial ratio people with overweight in neighborhood	-

C.7 Base case simulation

The results of the KPIs in the base case as depicted in Figure 4.26 and 4.27 show an increase in the number of overweight people in the neighborhood and the percentage of overweight people in the neighborhood, respectively. The behavior of the KPIs is endogenously determined by other variables in the model. This appendix will therefore further explain the behavior of certain variables in the model.

As indicated in the model conceptualization and model formalization parts, the number of overweight people increases as the average weight of people in the population increases. Figure C.4 shows that there is a gradual increase in the average weight of people in the neighborhood from 78.5 kg in 2015 to 79.6 kg in 2025.

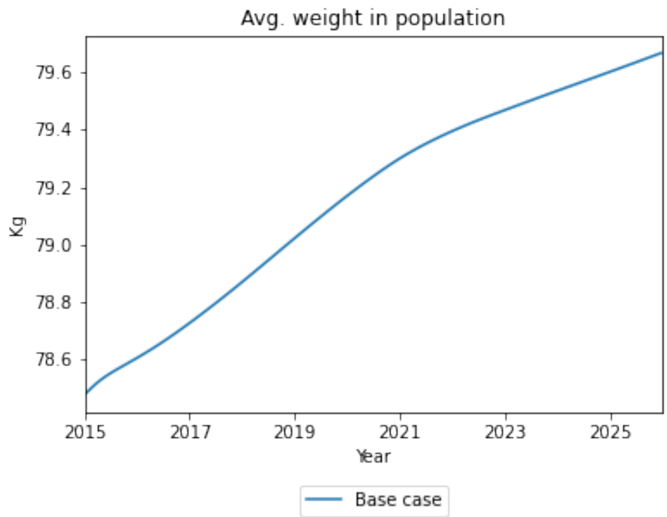


Figure C.4 Base case result of avg. weight in population

A positive value for the *energy imbalance*, see Figure C.5 (which is further explained below), is one of the causes of the observed weight gain in the model. In addition, smoking cessation also causes weight storage, given a decrease in the amount of smokers in the neighborhood, illustrated by Figure C.6.

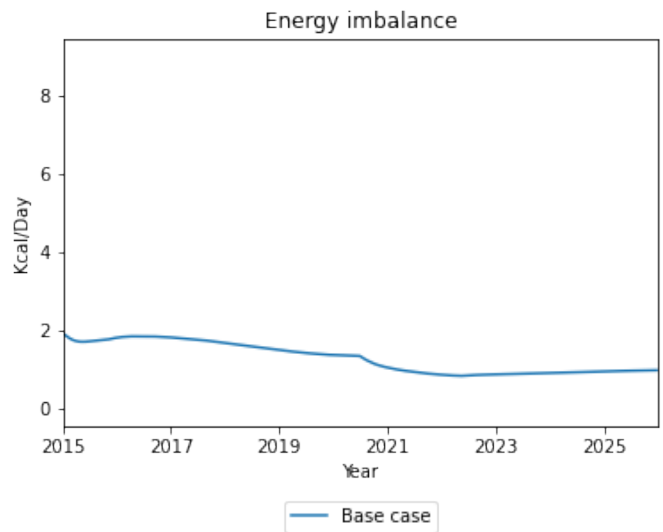


Figure C.5 Base case result of energy imbalance

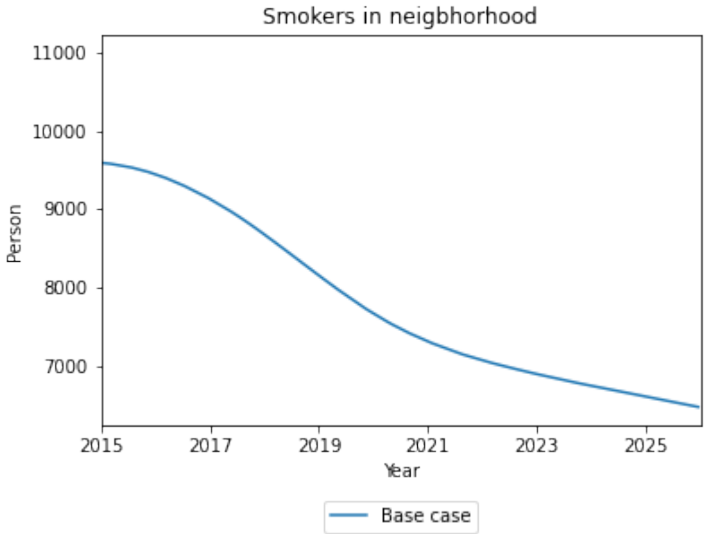


Figure C.6 Base case result of smokers in neighborhood

The positive *energy imbalance* is determined by the difference between energy intake, see Figure C.7, and energy expenditure, see Figure C.8. whose values both increase over the time. Both the intake and expenditure of kcal increase over time but the former does not exceed the latter, therefore the value of *energy imbalance* remains positive. The small nod at the beginning of the simulation in the graph of the *energy imbalance* occurs due to the delay of the *added weight per day* of which the initial value was set manually (see Table C25). The *energy imbalance* has a fairly constant value of around 1.7 kcal/day for the first five years of the simulation. In 2020, a kink is visible after which a new balance forms of around 1.5 kcal/day. This kink will be further explained by the variables that influence expenditure and intake.

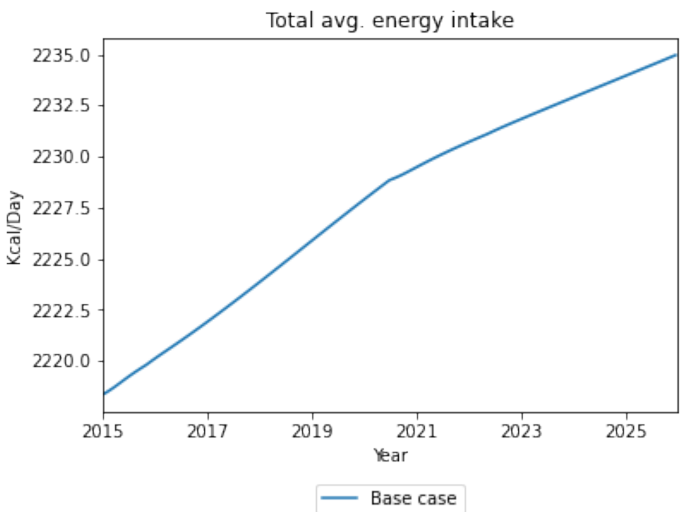


Figure C.7 Base case result of total avg. energy intake

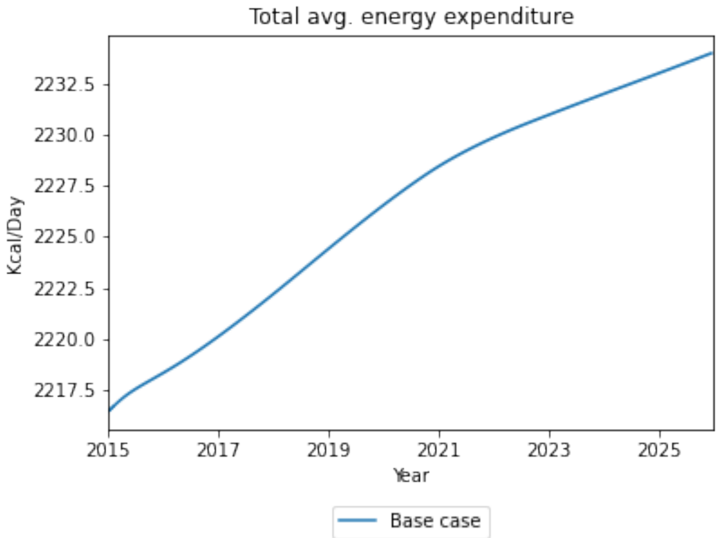


Figure C.8 Base case result of total avg. energy expenditure

The *total avg. energy expenditure* is determined by many model components. In order to explain the behavior of the energy expenditure parameter some of the model components are elaborated upon. First, energy expended during metabolism will be explained and subsequently aspects of energy expended during activity will be discussed.

As seen in Figure C.9, kcal expenditure increases during rest. This follows logically from the observed weight gain in Figure C.4.

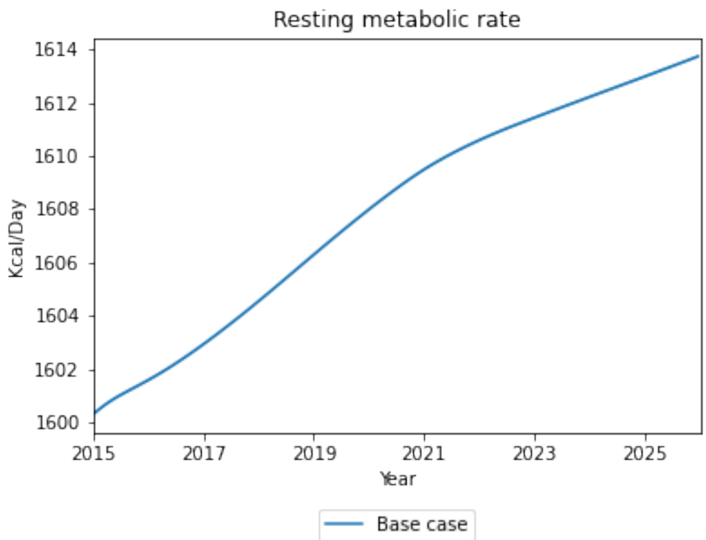


Figure C.9 Base case result of resting metabolic rate

The expenditure during activity thermogenesis is given in Figure C.10 and increases over time. This occurs partly due to the *avg. energy expenditure on exercise related activity* which also increases (see Figure C.11). The *avg. energy expenditure on exercise related activity* again consists of several model components of which *avg. energy expenditure with walking and cycling* is one (see Figure C.12). The increase of the variable *avg. energy expenditure with walking and cycling* is partly determined by an increase in *avg. walking time* as shown in Figure C.13. The reason for this is that the walking time of

Dutch and Western people in the model is higher, see figure C.14, and the proportion of these groups of people in the population increases, see figure C.15.

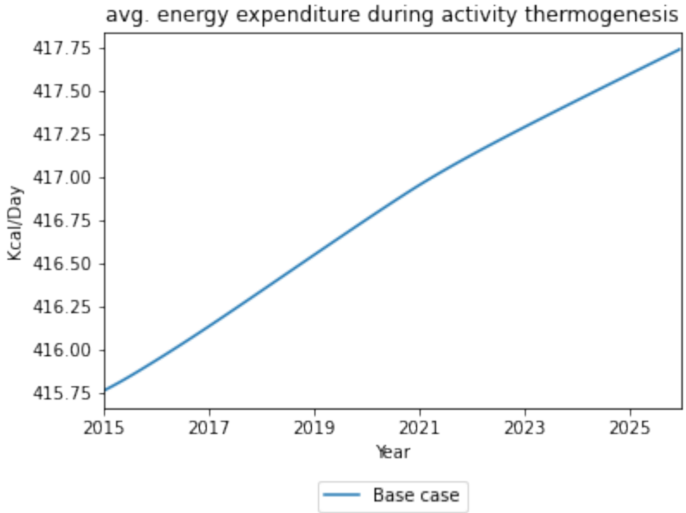


Figure C.10 Base case result of energy expenditure during activity thermogenesis

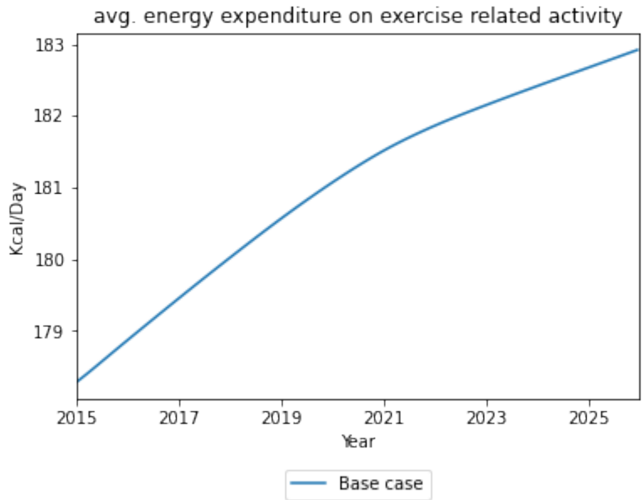


Figure C.11 Base case result of avg. energy expenditure on exercise related activity

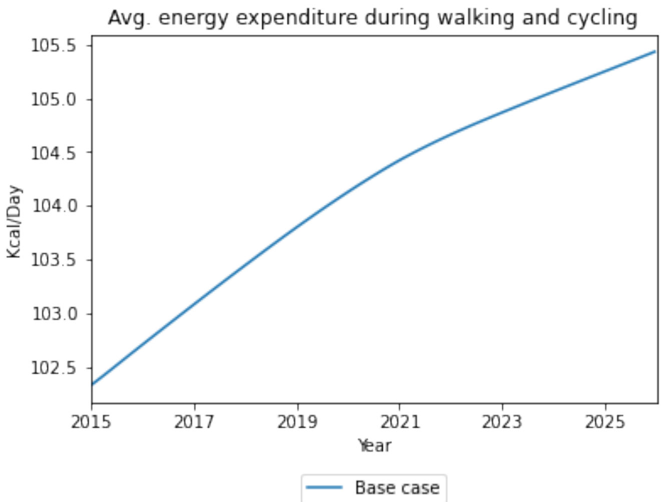


Figure C.12 Base case result of avg. energy expenditure during walking and cycling

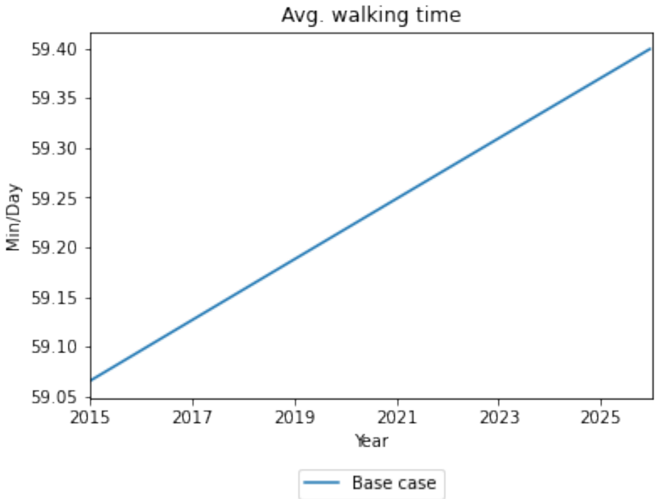


Figure C.13 Base case result of avg. energy expenditure during walking and cycling

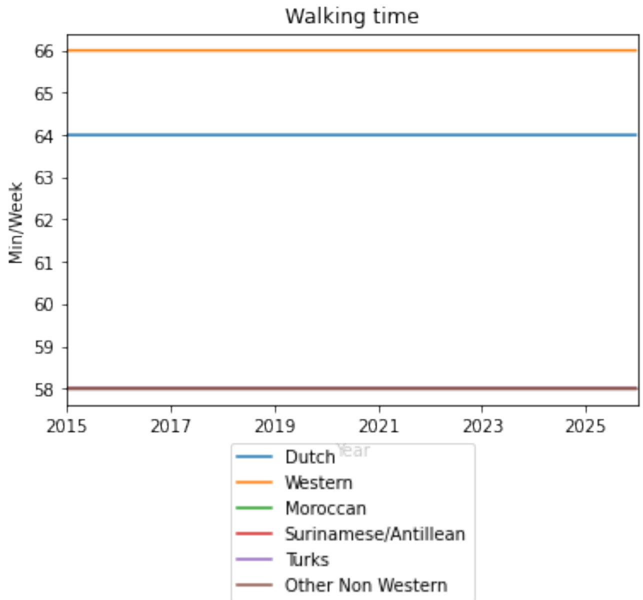


Figure C.14 Base case result of walking time[17]

[17] The values for the Moroccan, Surinamese / Antillean, Turkish and Other Non Western population groups have the same value.

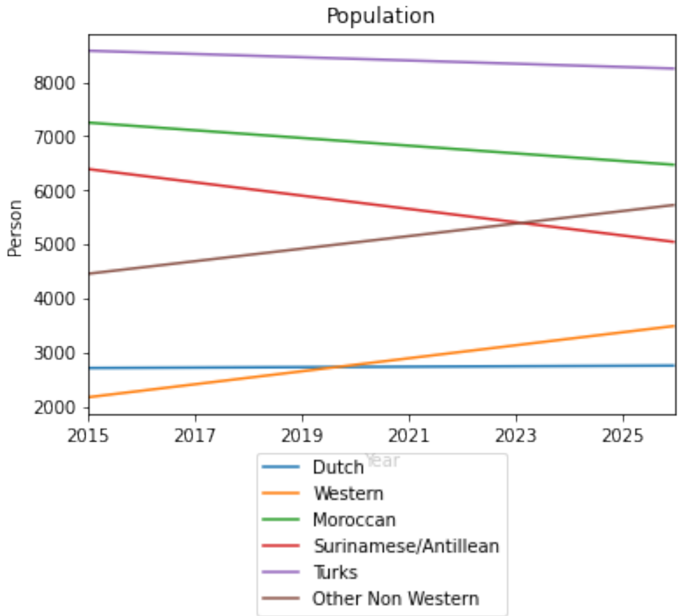


Figure C.15 Base case result of population

Another model component responsible for energy expenditure during activity is the energy expended during non-exercise related activity. The avg. energy expense during non-exercise related activities decreases over time, see Figure C.16. The reason that the energy expended during non-exercise related activities decreases and that of exercise related activities increases is explained by the difference in ratio with which these variables are influenced by activity level (0.7 and 0.3 respectively, see Appendix C.2).

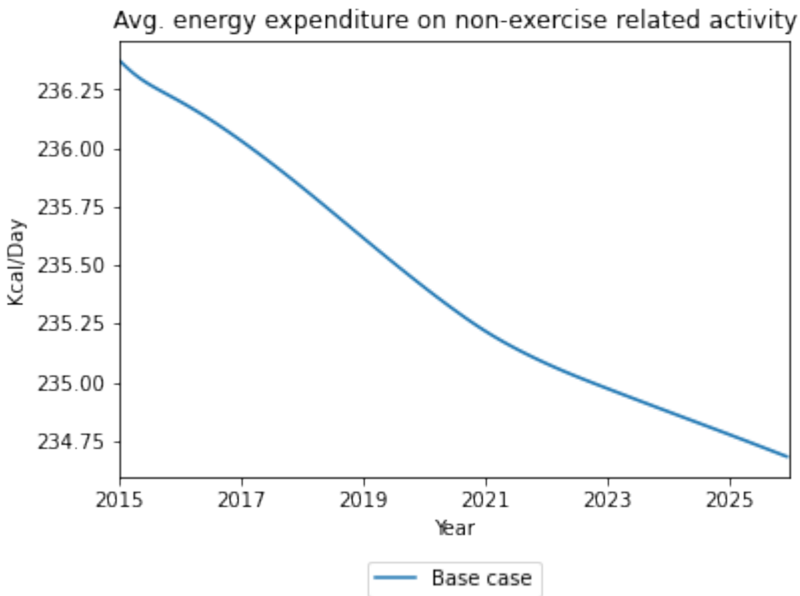


Figure C.16 Base case result of avg. energy expenditure on non-exercise related activity

The increase for total energy intake, which is shown in Figure C.7, also has several causes. The most important are discussed. As illustrated in Figure C.17, the food intake of food and non-alcoholic drinks remains the same over time. Figure C.18 provides insight into the kcal intake due to alcohol consumption and shows that this variable increases but the growth rate of the increase from 2020 onwards is smaller, this is explained by the reduced alcohol consumption from 2020 onwards, an assumption based on findings from RIVM (2020). This difference in the growth rate before and after 2020 determines the kink that is observed in the *total avg. energy intake* and thus *energy imbalance*. Figure C.19 shows that food intake due to an ultra-processed diet also increases over time.

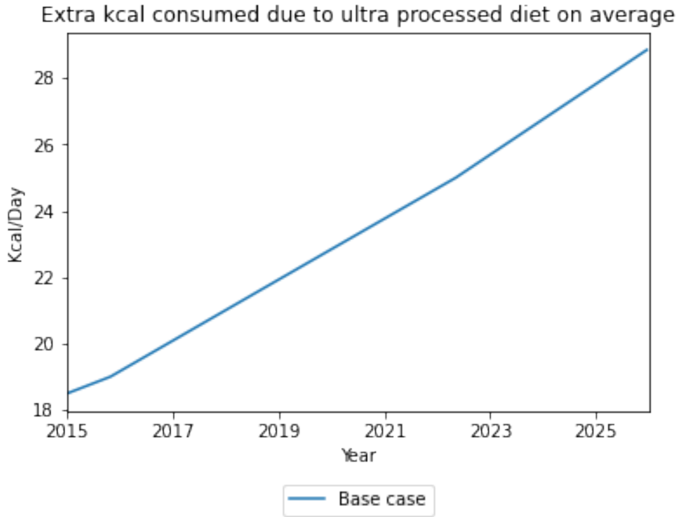


Figure C.17 Base case result of extra kcal consumed due to ultra-processed diet on average

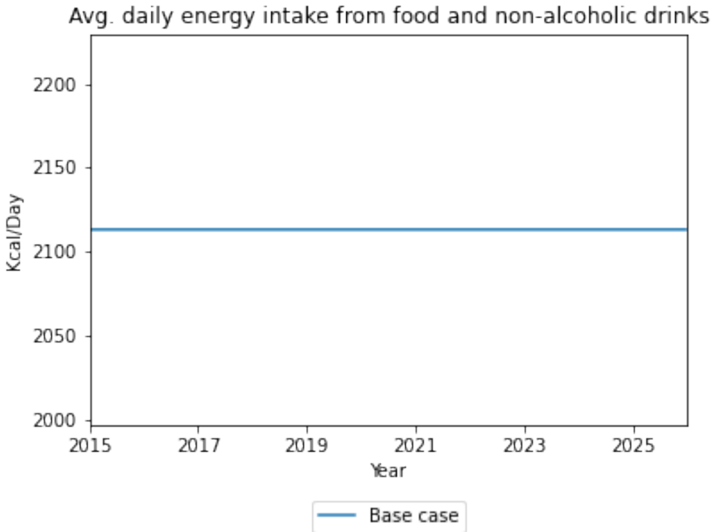


Figure C.18 Base case result of avg. daily energy intake from food and non-alcoholic drinks

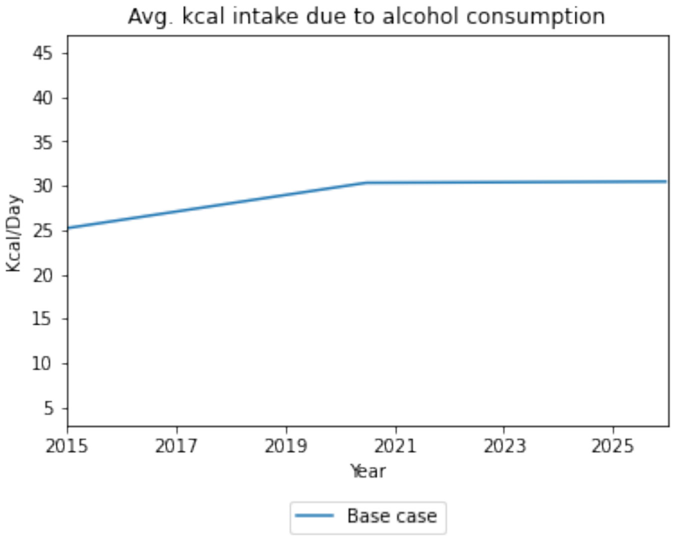


Figure C.19 Avg. kcal intake due to alcohol consumption

C.8 Python script for data visualization

The following script has been established for creating Figures in Python (version 3) to adjust the scale of the y-axis to year.

```
import numpy as np
import matplotlib.pyplot as plt

with open(r'./Name of table.txt') as f:
   data = f.read().split()
   n = 64001
   t = np.array(data[1:n])
   y1= np.array(data[int(n+1):int(2*n)])
   y2= np.array(data[int(2*n+1):int(3*n)])
   y3= np.array(data[int(3*n+1):int(4*n)])
   y4= np.array(data[int(4*n+1):int(5*n)])
   y5= np.array(data[int(5*n+1):int(6*n)])

   tf = t.astype(np.float)
   y1f= y1.astype(np.float)

   t_year = tf[:]/365+2015

plt.plot(t_year,y1f,label="Name of parameter")
plt.xlabel("Year")
plt.ylabel("Unit of parameter")
plt.title("Name of parameter")
plt.legend(bbox_to_anchor =(0.5,-0.3), loc='lower center')
plt.xticks([2015,2017,2019,2021,2023,2025,2027])
plt.xlim(2015,2026)
```

Appendix D. Verification & Validation of the model

D.1 Time step exploration

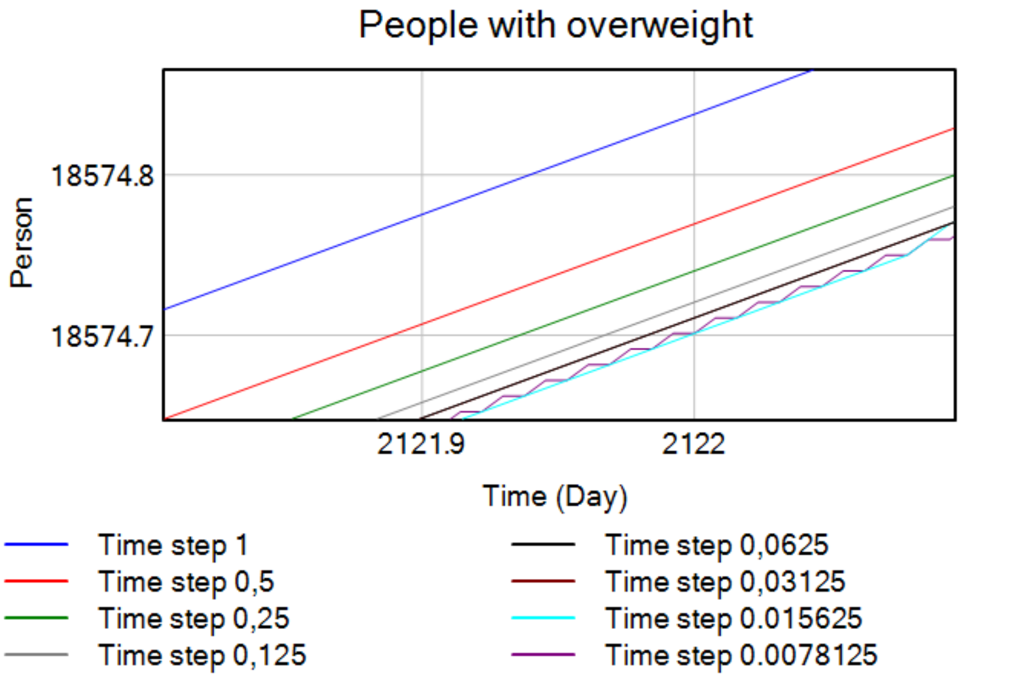


Figure D.1. Time step exploration

D.2 Extreme condition test

An extreme condition test was conducted to evaluate the structure of the model. New simulations are performed where extremely high and low values are inserted for some parameters. The effect of these changes on the KPI will be investigated. In this way it can be tested to what extent the model behaves realistically in extreme conditions. Different submodels are represented in five parameters, Table D1 provides an overview with the adjustments. The Figures in this section are retrieved from Vensim[18]

Table D1. Model parameter setting for the extreme condition test

Parameter	**Current Value**	**Low value**	**High value**
Initial population numbers[Ethnic groups]	2710, 2170, 7250, 6390, 8580, 4455	0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01	30.000, 30.000, 30.000, 30.000, 30.000, 30.000
Smoking cessation	WITH LOOKUP(Time) ([(0,0)-(10,10)] ,(0,0),(1,0.1729),(507.99, 0.846591),(959.536,1.3125),(1091.24,1.41477),(1335.82,1.46591),(1599.2	WITH LOOKUP(Time) ([(0,0)-(10,10)], (0,0),(9125,0)	WITH LOOKUP(Time) ([(0,0)-(10,10)], (0,5),(9125,5)

[18] The y-axis of the figures displayed by Vensim cannot be adjusted to years given the chosen time unit of the model in days. It is therefore important to note that day 0 corresponds to January 1, 2015 and day 4000 to December 31, 2025.

	3,1.40341),(1712.11,1.30114),(1937.89,1.0625),(2163.66,0.823864),(2596.39,0.511364),(3273.71,0.3863),(5117.53,0.3863),(9125,0.3863))		
Social cohesion	5.43	0	10
Degree of underreporting[Level of education groups]	0.03, 0.03, 0.03	0	0.5
Ratio additional intake of the difference	0.3	0	1

The following paragraphs describe the impact on the extreme values of the parameters on the systems behavior starting with an hypothesis. After conducting the tests, the behavior is compared to the hypothesis and is the model assessed for its ability to logically reproduce behavior.

D.2.1 Extreme high and low values for initial population numbers

For the extreme low value of the initial population 0.01 was chosen because 0.0 would cause problems for the calculation of other variables in the model (due to dividing by zero). The maximum values for the initial population is 30,000 for each population group which would mean around 6 times the current number of inhabitants.

Low values for the initial population will logically result in far fewer people being overweight. The reverse is true for high values. It is assumed that for both values there is some difference in the turnover of overweight people due to the fact that the ratio between the different ethnic population groups is different compared to the base case. In both cases, the proportion of people with a Dutch or Western background relative to the non-Western ethnicities has increased significantly. As a result, alcohol consumption will increase. In general, people of Western and Dutch origin exercise a little more, as a result of which the energy consumption through physical activity is expected to be slightly higher. Besides the fact that low and high values have an influence on the proportions, there is also a large influence on the total population. The strong increase in the total population, as in the case of high initial population values, will have a large influence on the number of unhealthy suppliers per 10,000 inhabitants where a decrease will be visible. The opposite happens with low initial population values and also this will bring about a much larger change given the large difference with the current initial values. It is expected that this effect on total intake will be stronger than the effect of changing alcohol consumption. How strong the differences in total energy consumption and intake are determines the weight gain, the course of the number of overweight people and thus the KPI percentage of overweight people.

The model gives an error at 0.01 as the value for the initial populations. The lookup function of the number of people with ultra-processed diets does not withstand these low values. This means that the model is not compatible in case of extremely low population values.

From a value of 6 onwards the lookup does work. The cause of the error is the extremity of the number of unhealthy suppliers per person. The lookup has a maximum value of 1 point of sale per person, which is already quite extreme. A solution to the error in this test is to extend the lookup to a higher number of suppliers per person, however, this would impair the visual clarity of the graph of the function.

Figure D.2 shows the effects of the change in values for the initial population, with 6 instead of 0.01 as the low values for the initial population. The number of overweight people changes as expected. And the percentage of overweight people can be attributed to the above hypothesis. The reason for the larger difference of the outcomes of extreme high value with the base case compared to the low values is due to the large difference between initial population numbers of the high extreme value compared to those of the base case.

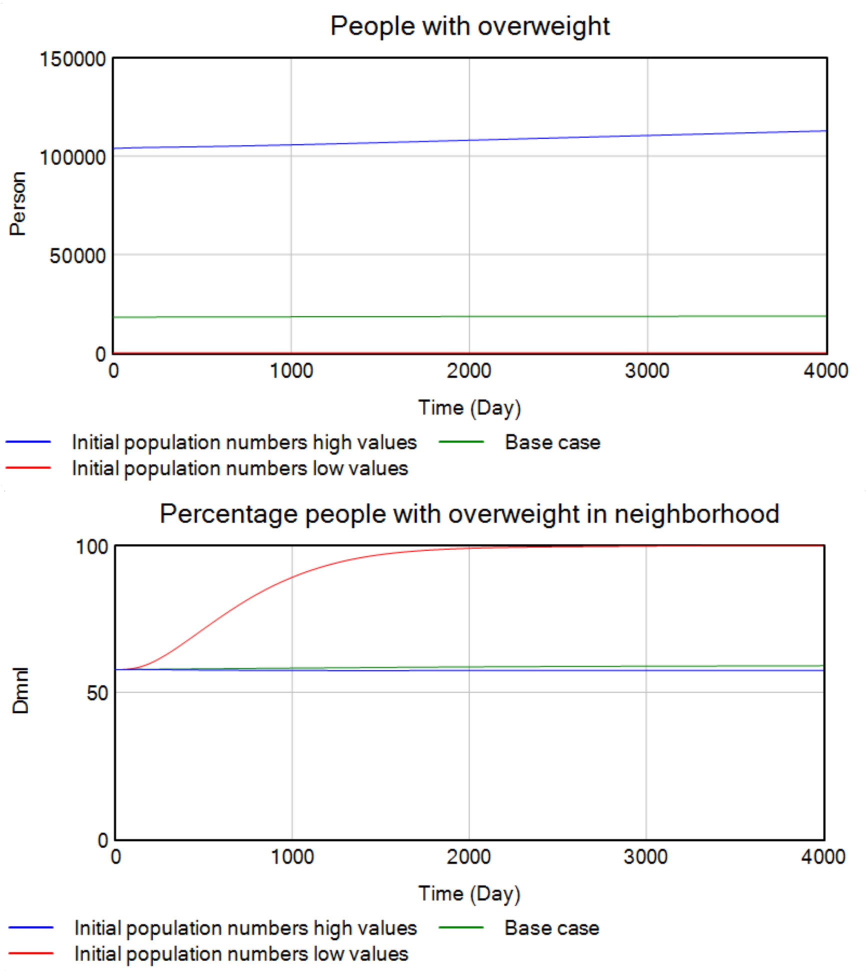


Figure D.2. Extreme value test initial population numbers

D.2.2 Extreme high and low values for smoking cessation

The smoking cessation variable represents the number of people who stop smoking per day and is determined by a lookup function with time as input. An extremely low value of 0 was chosen, over any point in time (i.e., for both day 0 and day 9125; the maximum value of the lookup).

It is expected that at a value of 0 there will be no weight gain resulting from smoking cessation. As a result, there will be fewer overweight people. On the contrary, at a value of 5, many more people are expected to become overweight as a result of the average weight gain from smoking cessation.

Figure D.3 shows the effects of the high and low values on the KPIs. The behavior corresponds to the expectations. The low value graph is closer to the base case because the extremely low values are closer to the base case lookup values compared to the extremely high values.

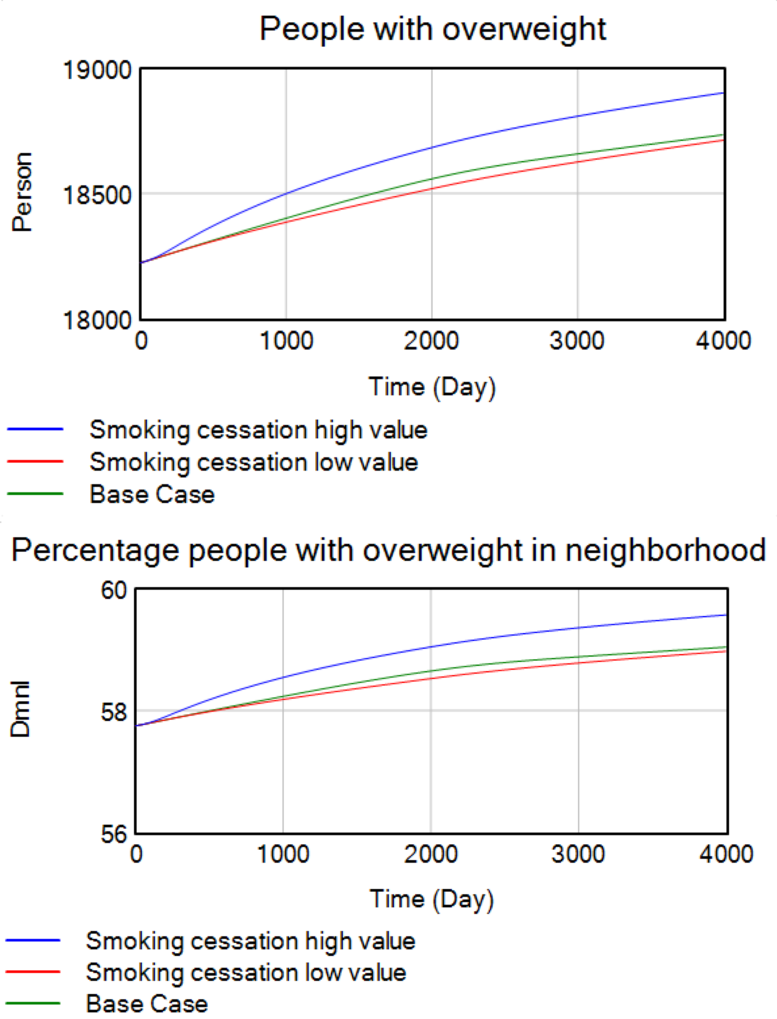


Figure D.3 Extreme value test annual percentage decrease smokers

D.2.3 Extreme high and low values for the degree of social cohesion

The degree of social cohesion is determined by the municipality on a scale of 0 to 10. These values were applied as low and high values for this test.

Social cohesion reinforces the degree of physical activity. It is therefore stated that in case of no social cohesion in a neighborhood there is less physical activity which increases the number of overweight people. The reverse is true for ultimate social cohesion in a neighborhood, corresponding to a value of 10. The expectation is that there will not be large differences in the model KPIs since social cohesion is not a major predictor of becoming overweight.

The hypothesis described in the paragraph above is in line with the results of the test shown in Figure D.4.

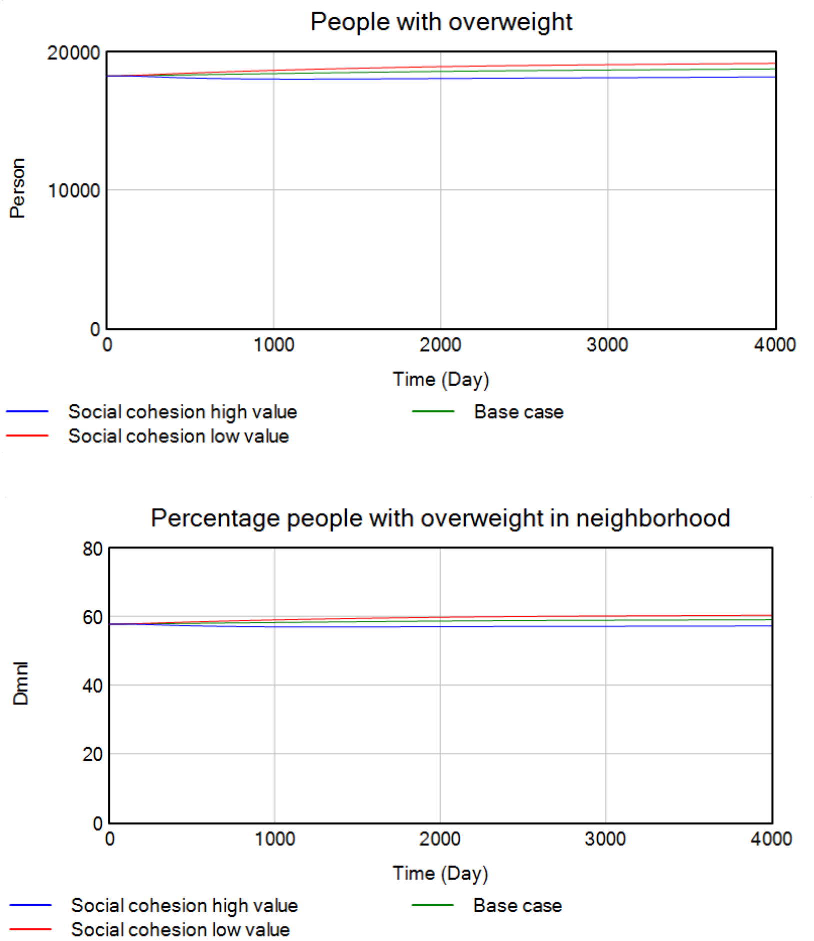


Figure D.4. Extreme value test social cohesion

D.2.5 Extreme high and low values for the degree of underreporting

It is possible that there is no underreporting, corresponding to a value of 0. Also, in an exceptional case, there could be an underreporting of 0.5, which means that people consume half a time more food than what they actually report. 0.5 is seen as a maximum because the results of the survey otherwise differ so greatly from previous national values that it does not provide enough reliability to serve as a data source. A value of zero for underreporting is expected to lead to a lower value for the variable total average energy intake in the model causing a decrease of overweight in the population. A high value for underreporting will have the opposite effect. At the same time, with this high value there will be a larger discrepancy with the base case because of the large difference between the high values and the current value. The elevated level of overweight at extreme values of underreporting are attributable to the large increase in energy intake that appears in the model in this case compared to the base case. Therefore, this behavior can be considered plausible.

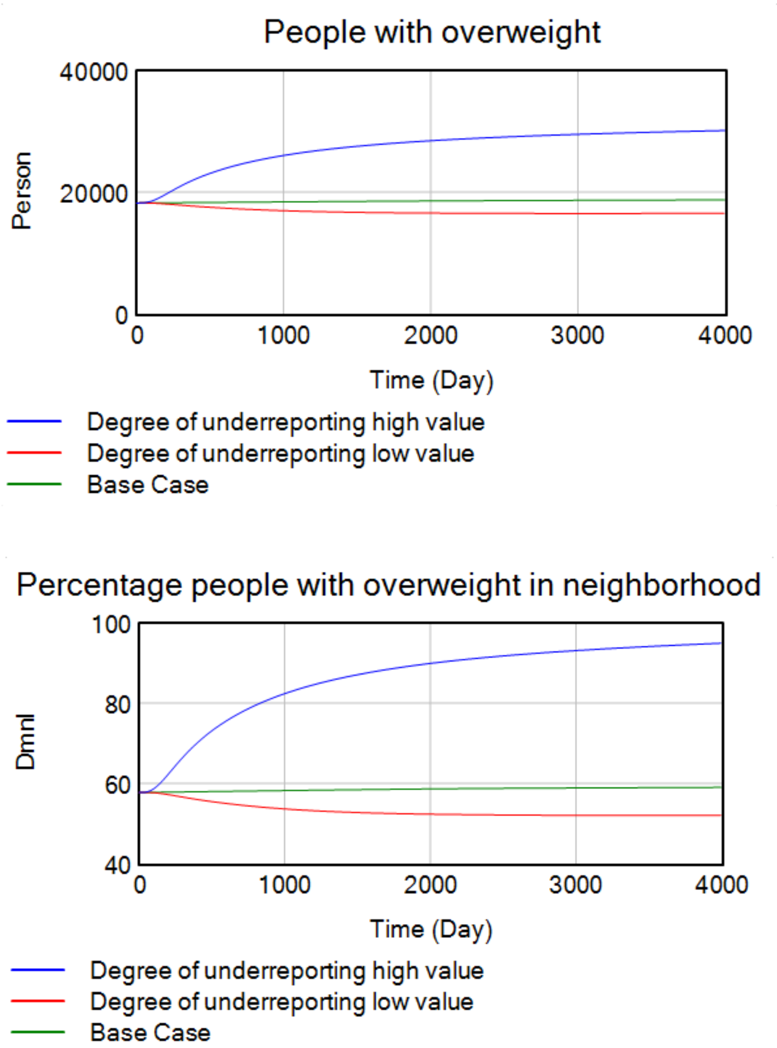


Figure D.5. Extreme value test degree of underreporting

D.2.6 Extreme high and low values for the ratio physiologically determined intake

The degree to which intake is determined by physiology could be either 0 or 1 in extreme cases. In the case where intake is not physiologically determined at all, intake will not respond to change in energy expenditure. It is expected that more overweight will be present because a decrease in expenditure is not balanced by less food consumption. In the case of intake being completely physiologically determined it is expected that less will be overweight given the fact that changes in energy expenditure are fully balanced with respective changes in intake.

The results of the extreme condition test depicted in Figure D.6 are consistent with expectations. The reason that the low values for the physiological determination of intake are a lot closer to the base case than the high extreme values is due to the feedback mechanisms occurring in the system. The feedback mechanisms in the model that are involved in weight change also ensure a balanced effect. Therefore, in the absence of physiologically driven intake, there will still be a balanced effect of energy imbalance due to adjustments in human metabolism.

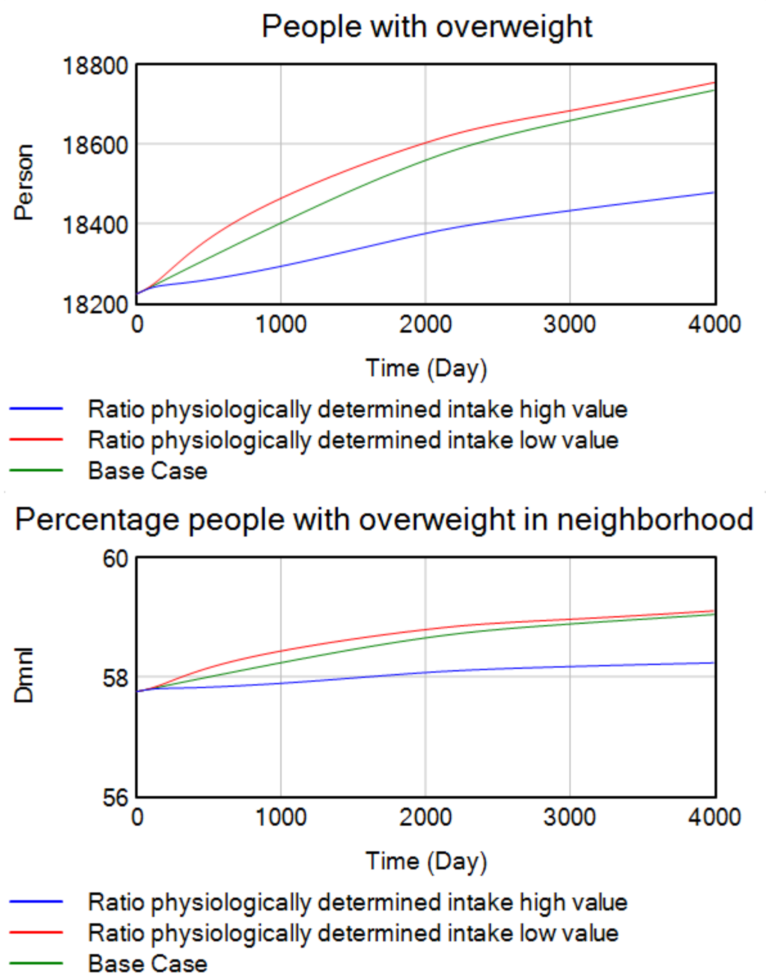


Figure D.6. Extreme value test for ratio physiologically determined intake

D.3 Sensitivity analysis

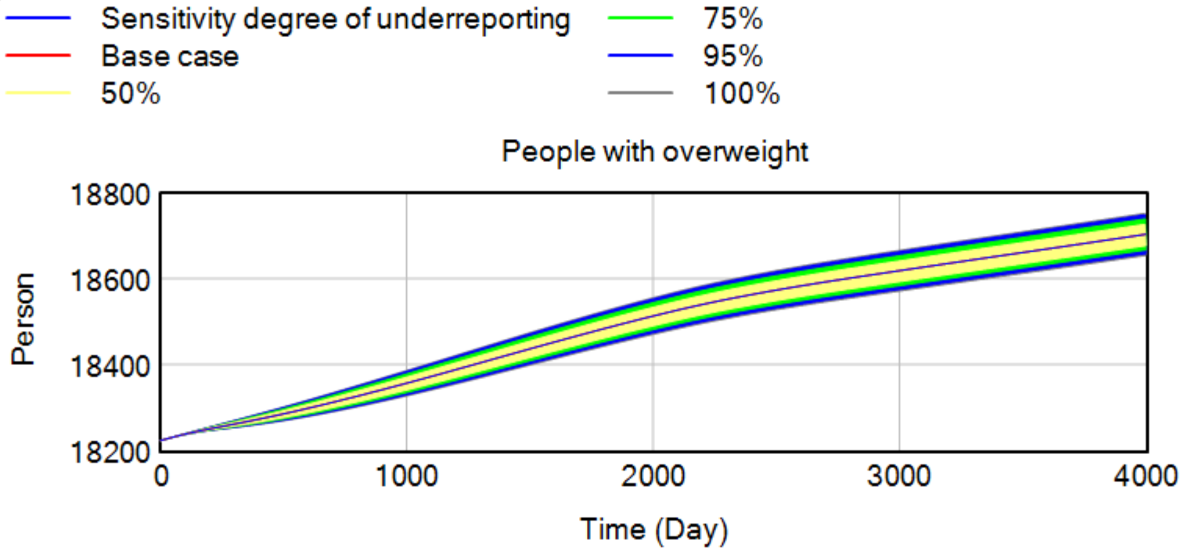
Table D2 shows the values implemented for the sensitivity analysis which is performed using Vensim's built-in test. The figures below[19] show the results of the sensitivity analysis on the KPIs and are categorized by tested parameters.

Table D2. Input parameters and corresponding values for sensitivity analysis

Parameter	Current value	- 10 %	+ 10 %
Degree of underreporting	0.03, 0.03, 0.03	0.027, 0.027, 0.027	0.033, 0.033, 0.033
Ratio physiologically determined intake	0.5	0.45	0.55
MET value during sport activity	7	6.3	7.7
Annual increase unhealthy food suppliers	0.5	0.45	0.55
Initial ratio people with overweight	0.5775	0.51975	0.63525

[19] The dataset of the sensitivity runs are too large to be fully accessed in Excel. In addition, opening these files in Python requires a lot of computing power. Therefore, the figures provided by Vensim are shown. It is not possible to adjust the unit of the y-axis of the figures in Vensim to years given the chosen time unit of the model in days. It is therefore important to note that day 0 corresponds to January 1, 2015 and day 4000 to December 31, 2025.

D.3.1 Sensitivity analysis degree of underreporting



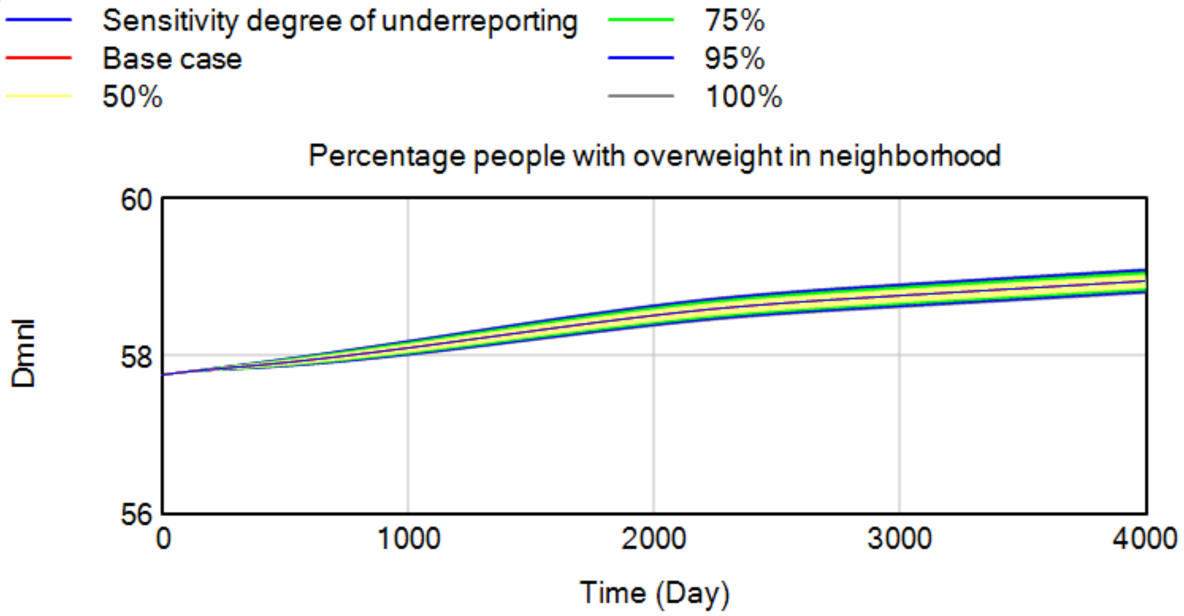
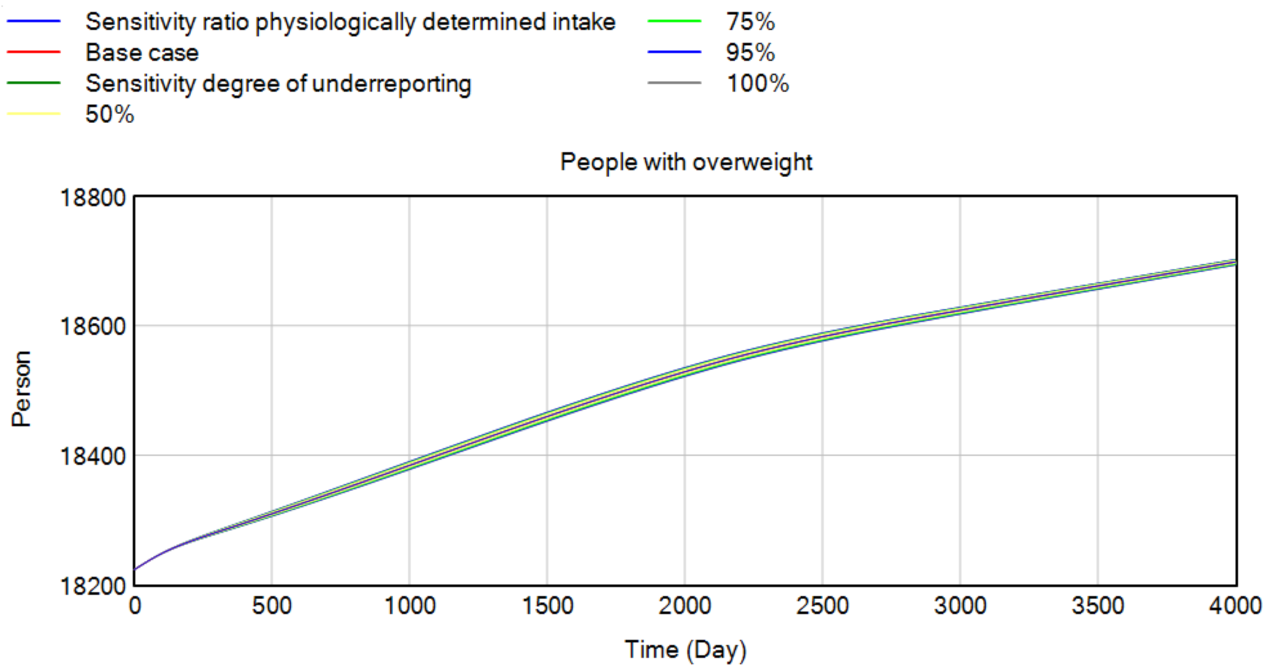


Figure D.7. Sensitivity of degree of underreporting

D.3.2 Sensitivity analysis ratio physiologically determined intake



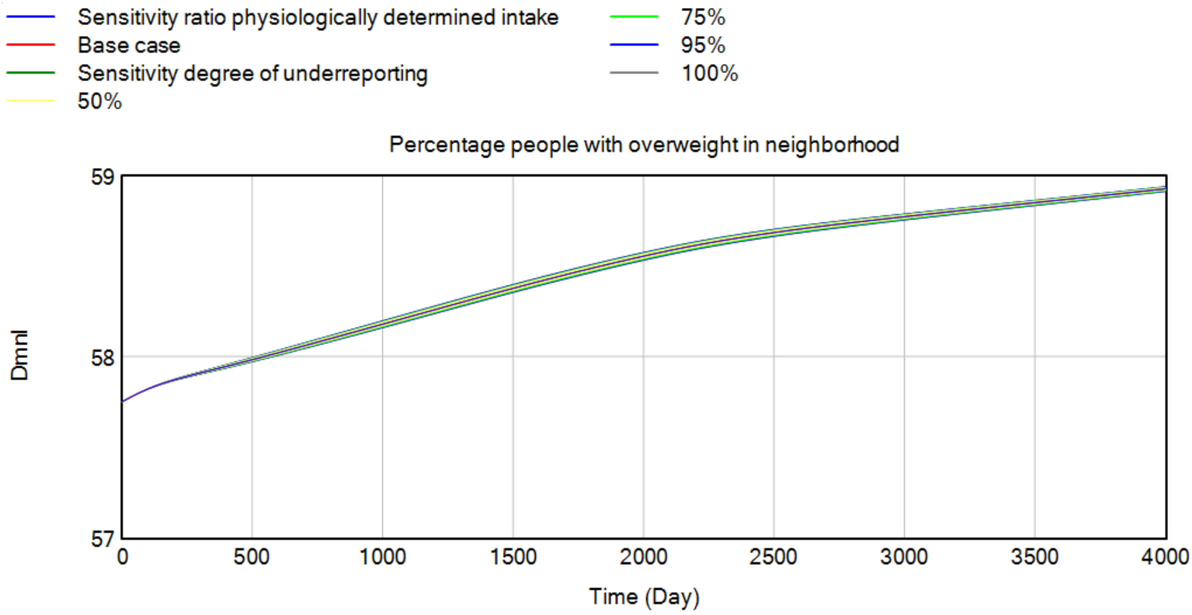
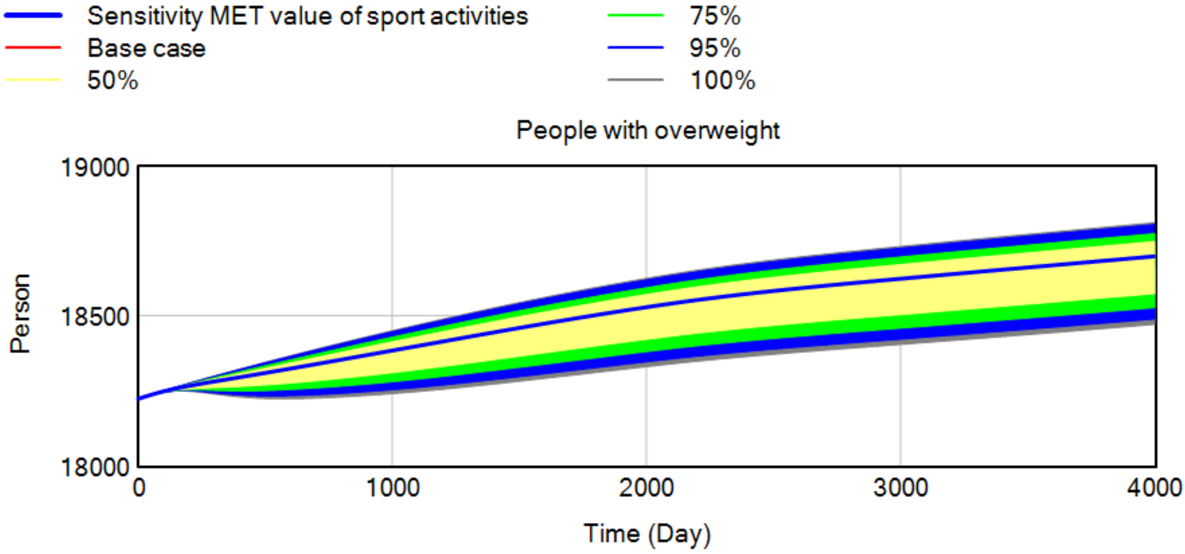


Figure D.8. Sensitivity of ratio physiologically determined intake

D.3.3 Sensitivity analysis MET value of sport activities



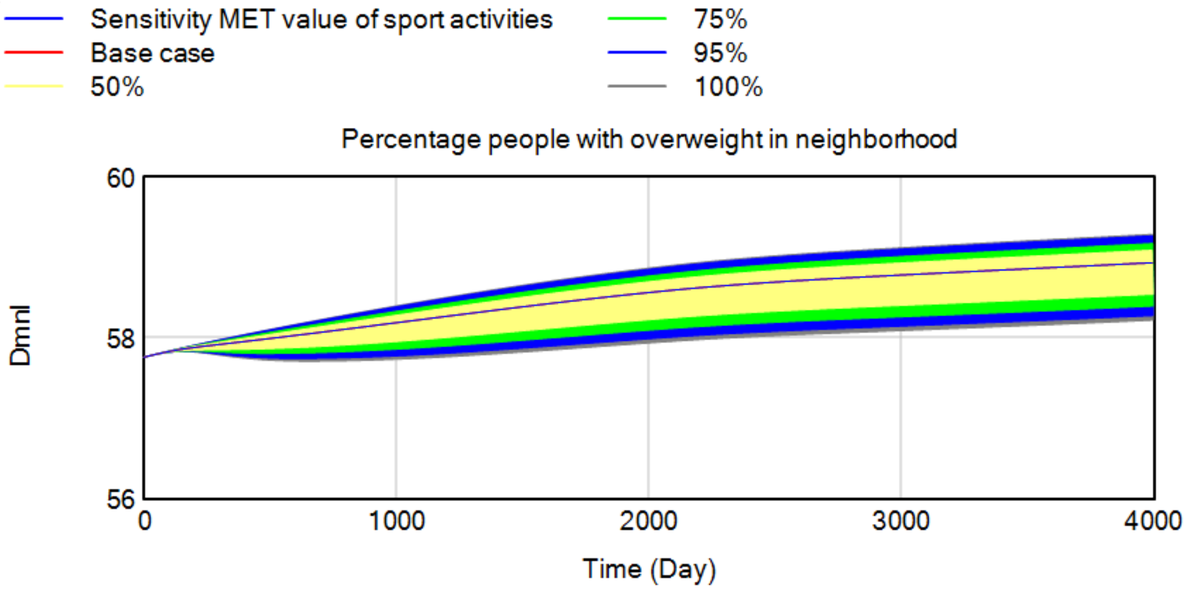
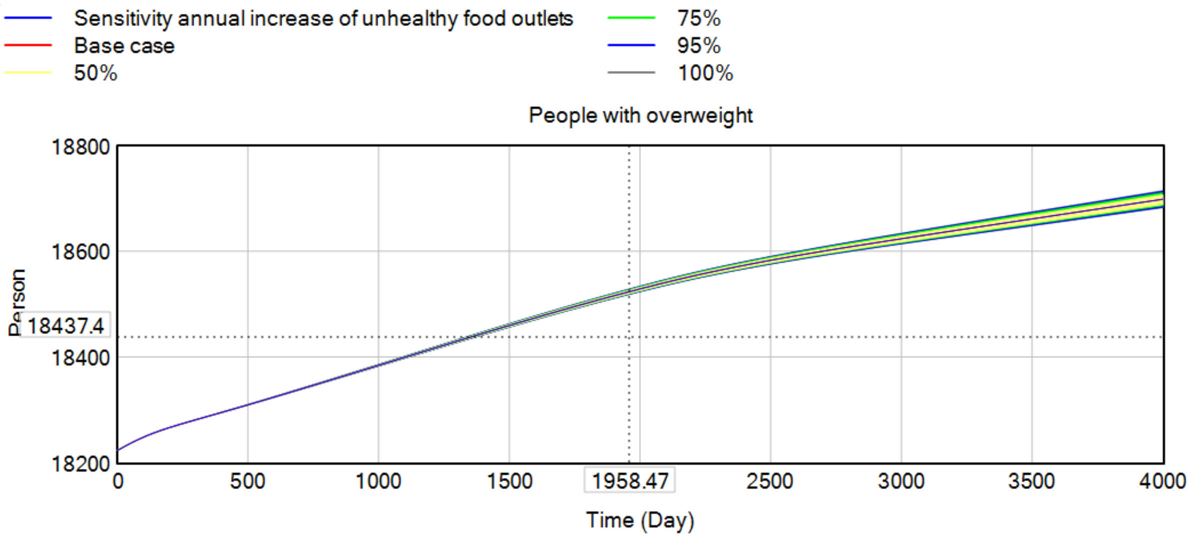


Figure D.9. Sensitivity of MET value of sport activities

D.3.4 Sensitivity analysis annual increase of unhealthy food suppliers



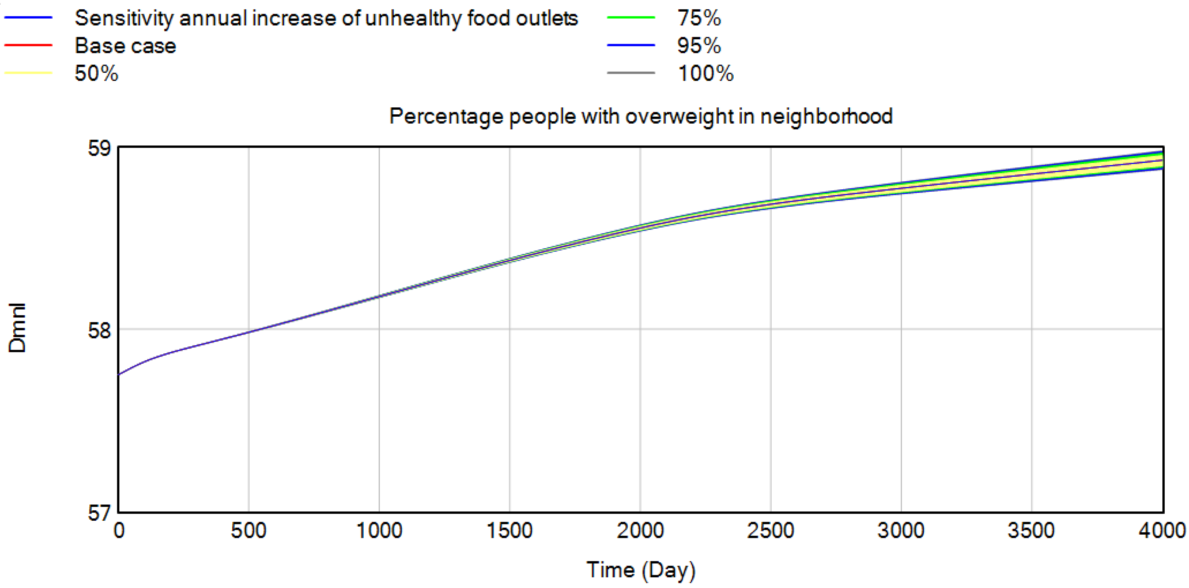
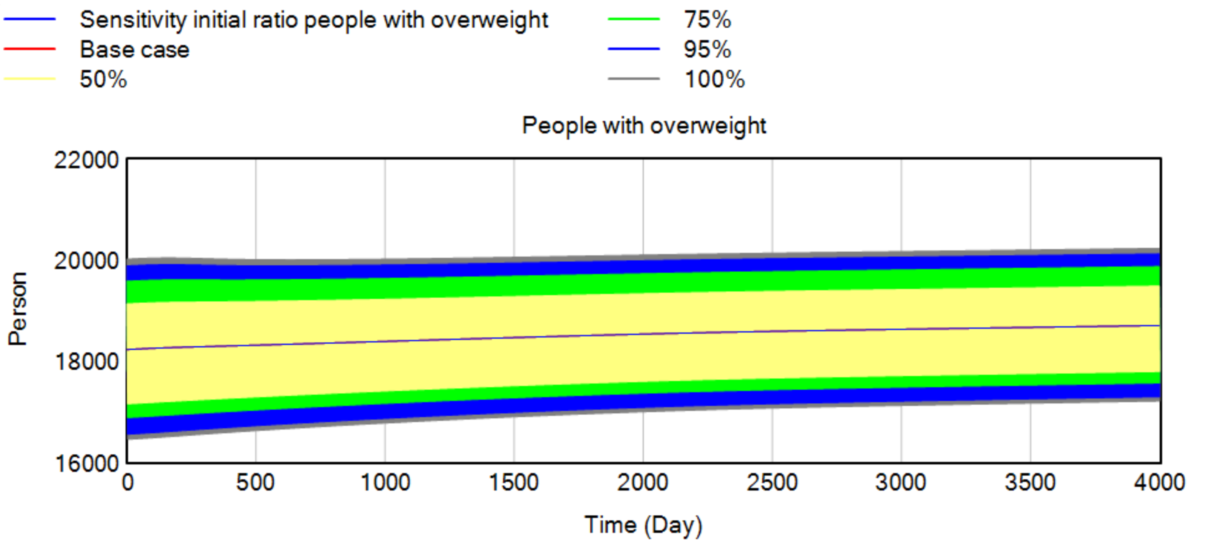


Figure D.10. Sensitivity annual increase of unhealthy food suppliers

D.3.5 Sensitivity analysis Initial ratio people with overweight in the neighborhood



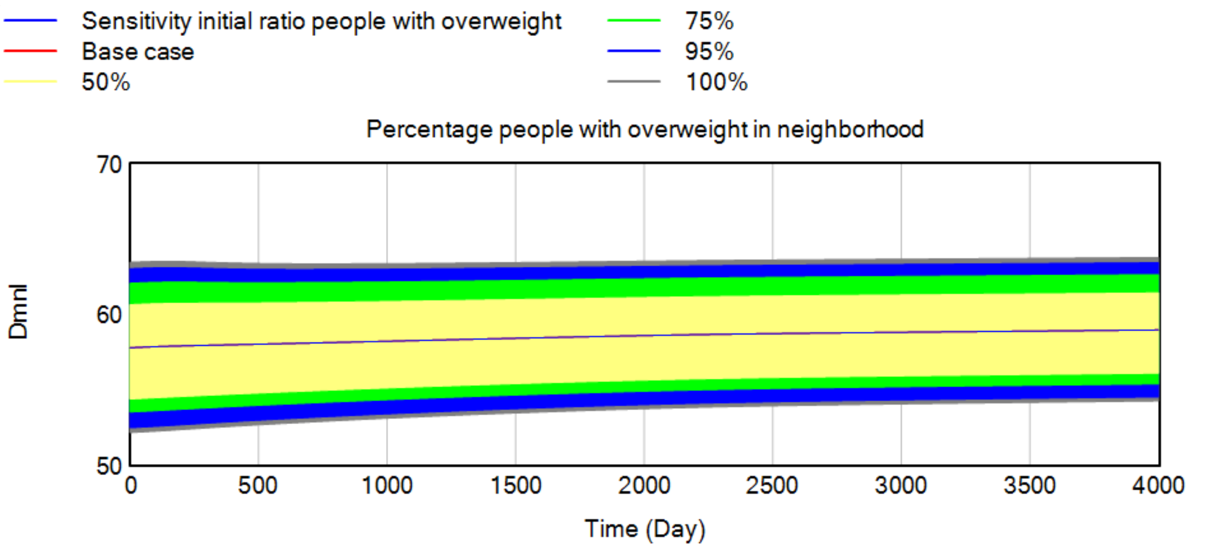


Figure D.11. Sensitivity probability people moving to the neighborhood having a healthy weight

Appendix E. Experimental Setup

E.1 Uncertainty analysis

The parametric uncertainty analysis provides insight into the range of possible model outputs. For each uncertain parameter, a range of high and low values is determined in which the value of the parameter is likely to occur in reality. These values are shown in Table E1.

Table E1. Uncertainty analysis parameter values

Parameter	Unit	Current value	Lower value	Upper value
Additional physical activity per unit increase of social cohesion	Min/Day	1	0	3
Avg. MET value during NEAT activities	Dmnl	0.8	0.6	1.0
Walking time[Ethnic Group]	Min/Week	64,66,58,58,58,58	57, 57, 57, 57, 57, 57	66, 66, 66, 66, 66, 66
Cycling time[Ethnic Group]	Min/Week	78,70,52,52,52,52	52, 52, 52, 52, 52, 52	78, 78, 78, 78, 78, 78
Avg. MET value of sport activities	Dmnl	6	6.8	8.5
Decrease in minutes per day spent on activity per kg increase in weight	Min/Dag/Kg	5.6	5	6
Reduced expense on kcal per reduced number of minutes per day on activity	Kcal/(Min/Day)	2.38	2	2.5
Ratio physiologically determined intake	Dmnl	0.5	0.3	0.6
Degree of underreporting in food consumption survey	Dmnl	0.03, 0.03, 0.03	0.02, 0.02, 0.02	0.04, 0.04, 0.04
Annual increase of unhealthy food suppliers	Supplier/Year	0.5	0.3	0.7
Dutch average ratio of people having an ultra-processed diet	Dmnl	0.02	0.025	0.03

E.2 Results uncertainty analysis

The Figures in this section[20] show the effect of adjustments of the aforementioned parameters on the KPIs.

E.2.1 Uncertainty analysis additional physical activity per unit increase of social cohesion

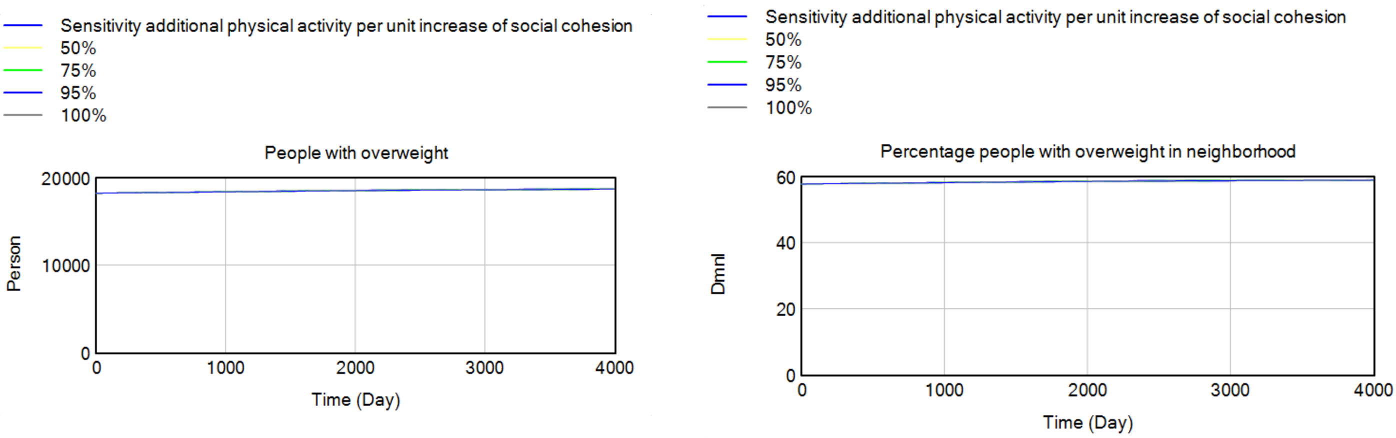


Figure E.1. Sensitivity additional physical activity per unit increase of social cohesion

E.2.2 Uncertainty analysis avg. MET value during NEAT activities

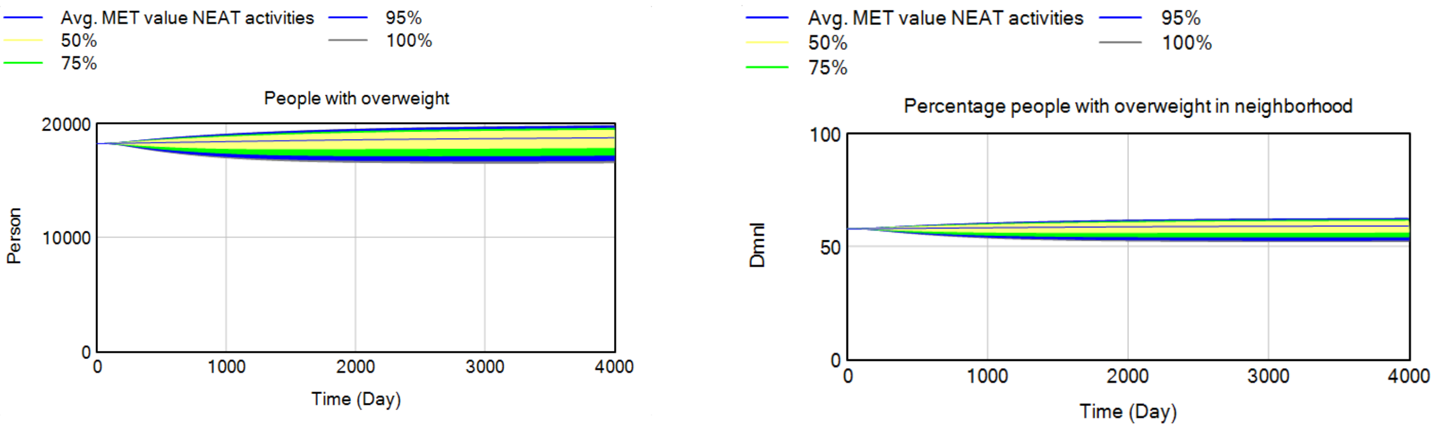


Figure E.2. Sensitivity avg. MET value during NEAT activities

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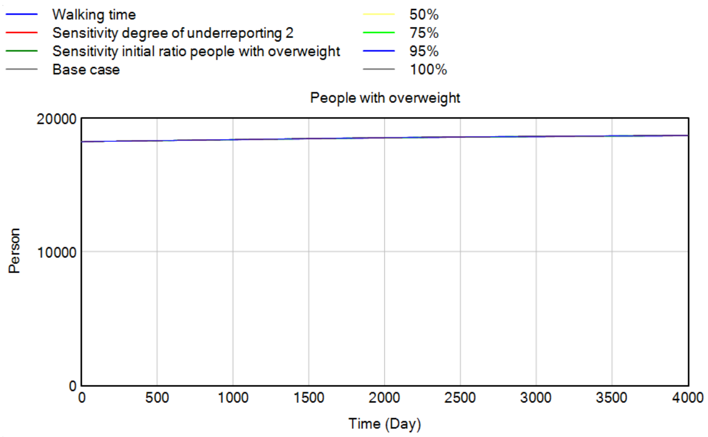
[20] The dataset of the sensitivity runs are too large to access in Excel. In addition, opening these files in Python requires a lot of computing power. Therefore, the figures provided by Vensim are shown. It is not possible to adjust the unit of the y-axis of the figures in Vensim to years given the chosen time unit of the model in days. It is therefore important to note that day 0 corresponds to January 1, 2015 and day 4000 to December 31, 2025.

E.2.3 Uncertainty analysis walking time



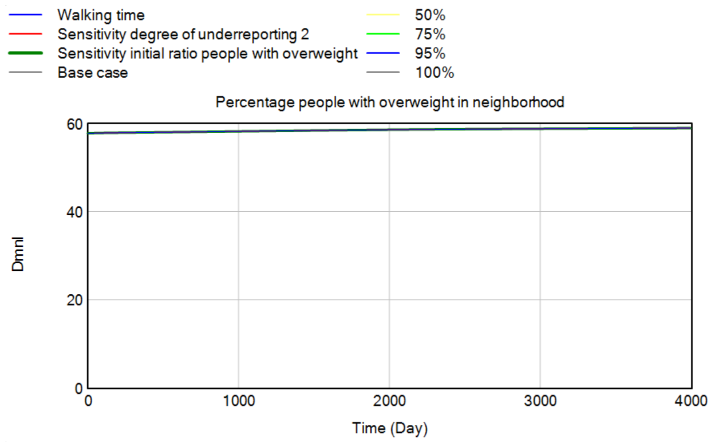
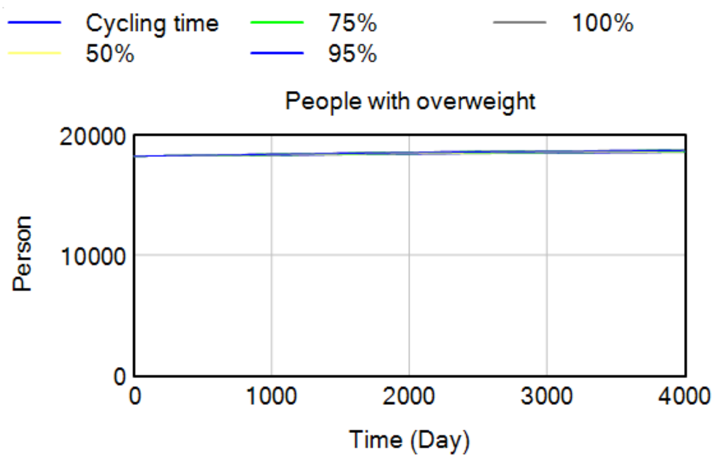


Figure E.3. Sensitivity walking time

E.2.4 Uncertainty analysis cycling time



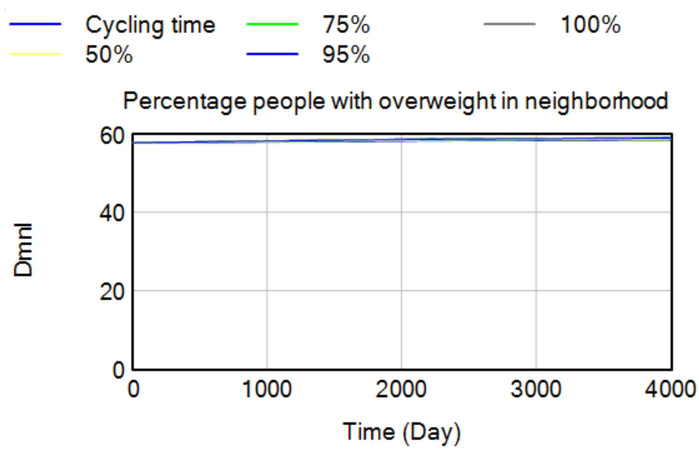
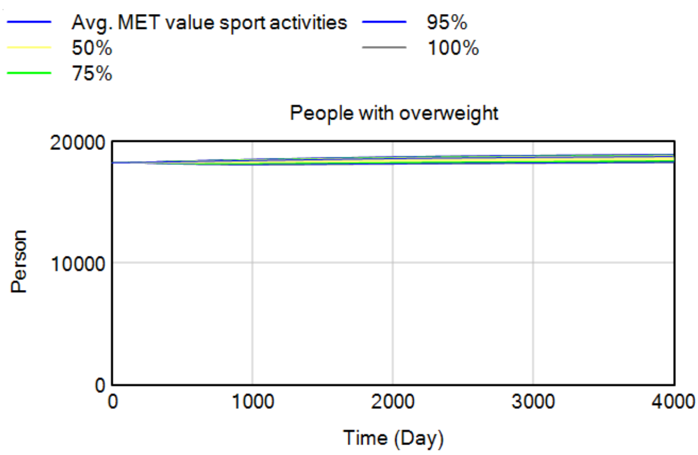


Figure E.4. Sensitivity cycling time

E.2.5. Uncertainty analysis avg. MET value of sport activities



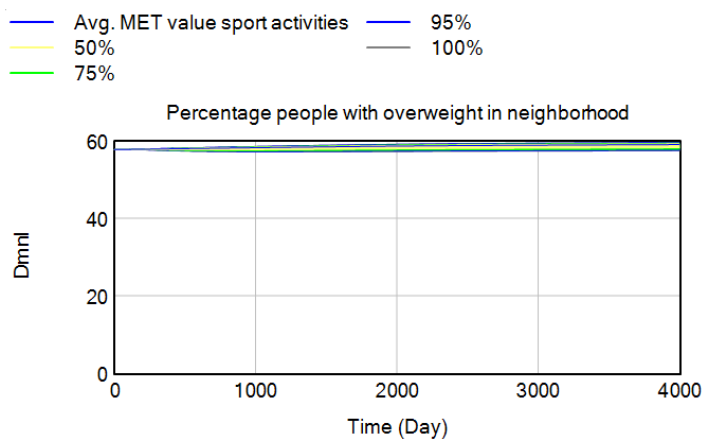


Figure E.5. Sensitivity Avg. MET value of sport activities

E.2.6 Uncertainty analysis decrease in minutes per day spent on activity per kg increase in weight

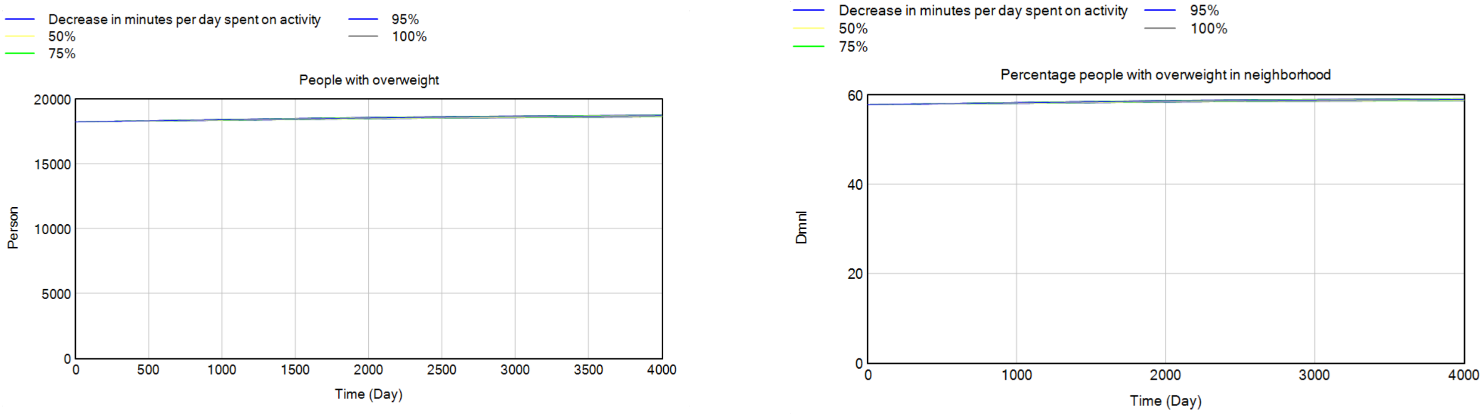


Figure E.6. Sensitivity decrease in minutes per day spent on activity per kg increase in weight

E.2.7 Uncertainty analysis reduced expense on kcal per reduced number of minutes per day on activity

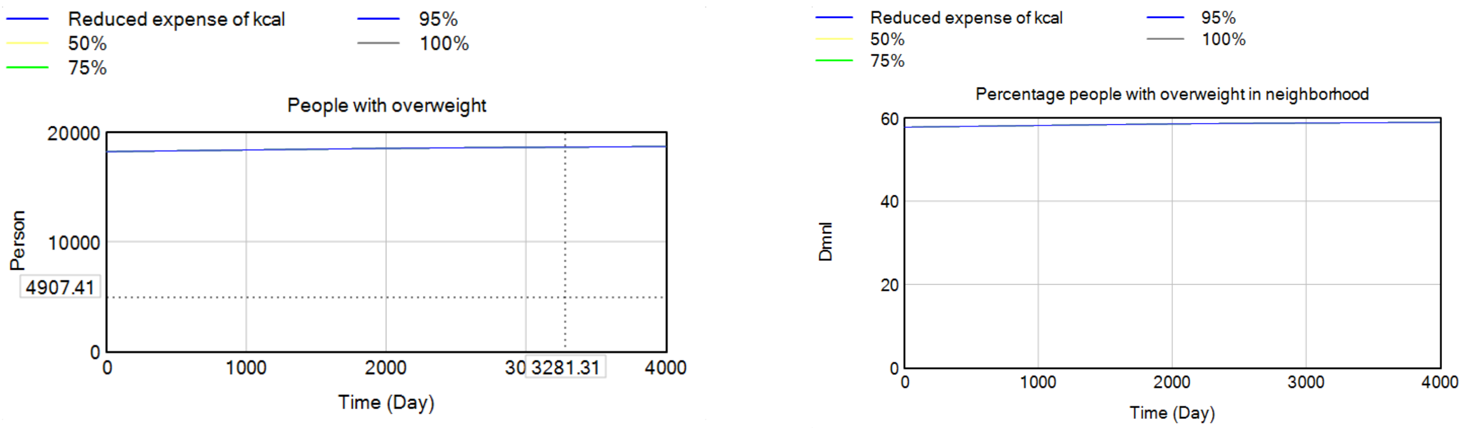


Figure E.7. Sensitivity reduced expense on kcal per reduced number of minutes per day on activity

E.2.8 Uncertainty analysis ratio physiologically determined intake

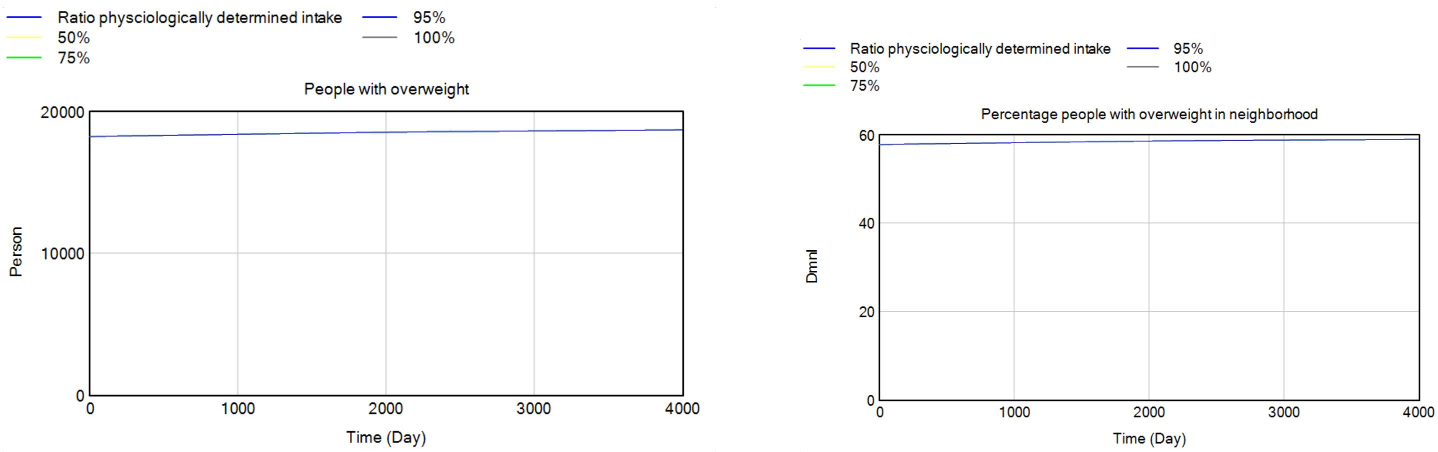


Figure E.8. Sensitivity ratio physiologically determined intake

E.2.9 Uncertainty analysis degree of underreporting in food consumption survey

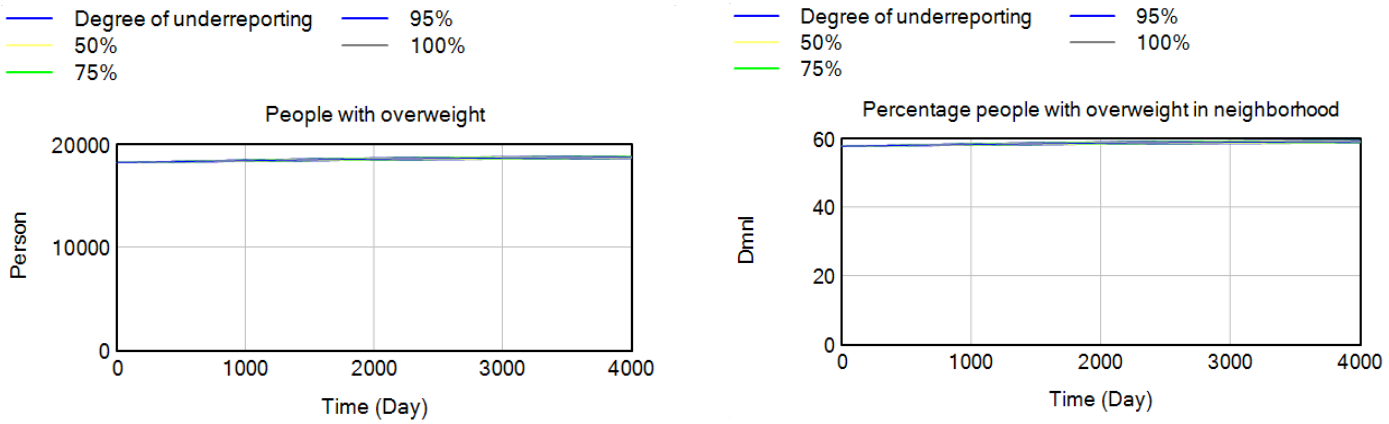


Figure E.9. Sensitivity degree of underreporting

E.2.10 Uncertainty analysis annual increase of unhealthy food suppliers

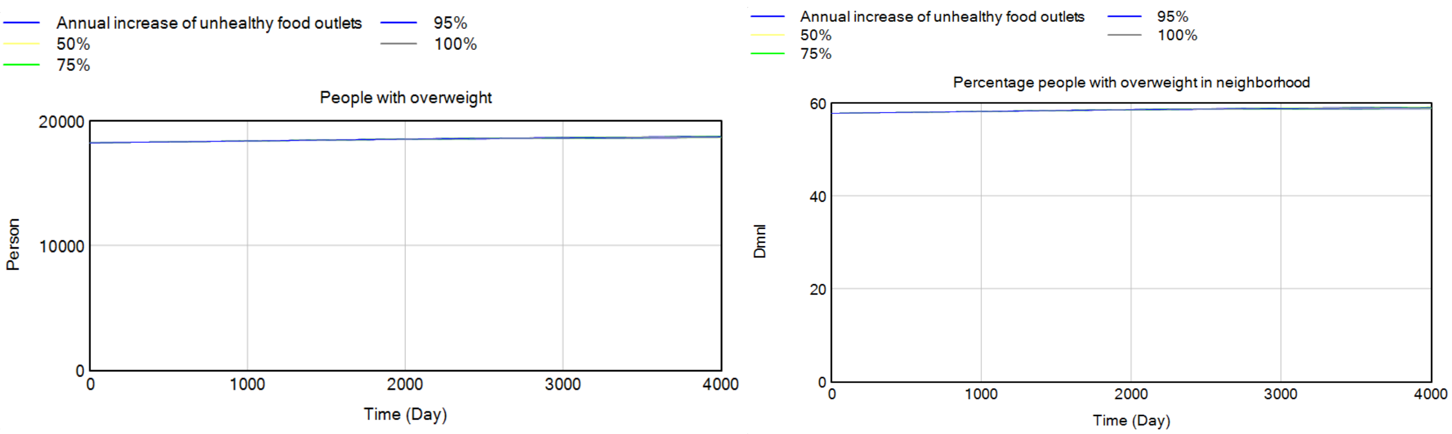


Figure E.10. Sensitivity unhealthy food suppliers

E.2.11 Uncertainty analysis Dutch average ratio of people having an ultra-processed diet

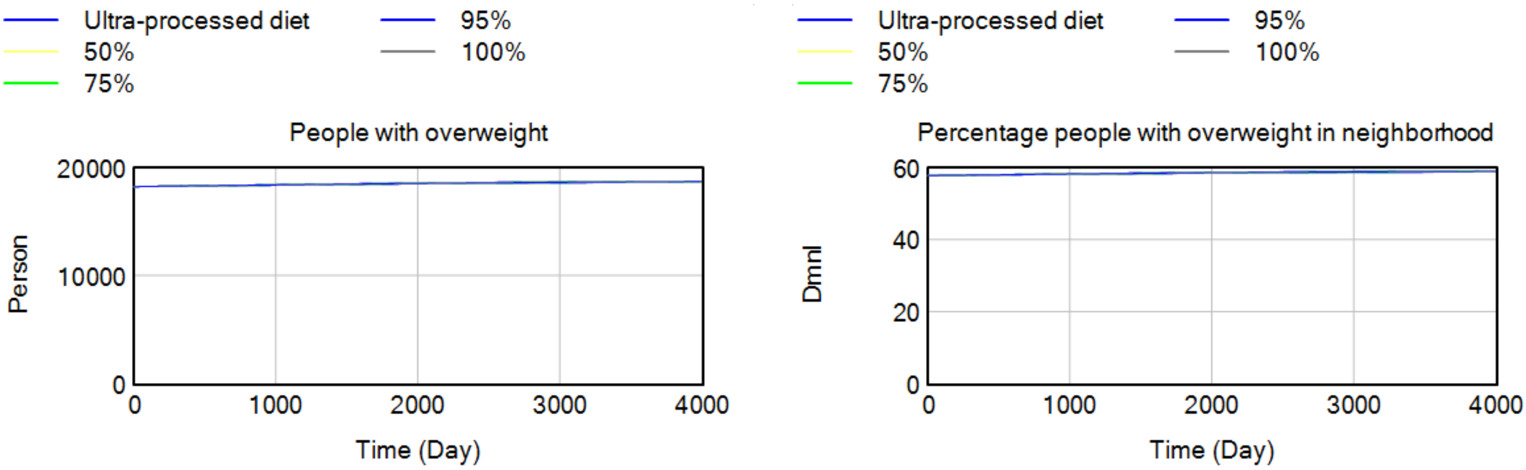


Figure E.11. Sensitivity dutch average ratio of people having an ultra-processed diet