Beyond diet and exercise:
A system dynamics approach to understanding the relationships between weight and well-being

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Figures

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Dedications

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Abstract

Over the past decade, the province of British Columbia has experienced undesirable rates of overweight and obesity among its residents. These rates result in challenges for both overweight and obese individuals, as well as for health care practitioners and policy makers. The objective of the thesis was to look beyond the generally accepted influencers of weight (diet and exercise) and develop greater insight into the causal relationships among factors that influence one's weight and well-being. System dynamics methodology was applied to construct a simulation model that investigates the underlying system structure of such relationships. The model serves as a dynamic hypothesis addressing how feedbacks between individual and environmental factors impede one's ability to maintain a healthy weight. The simulation model serves to aid policy makers in improving their understanding of the current system and to aid in the identification of policy leverage points to halt or reverse the obesity trend.

1. Problem Description

1.1 Current State In Canada

In 2005, over half of Canadian adults self-reported being overweight or obese according to their body mass index (BMI) (1). One's BMI is an indicator of body adiposity and is calculated by dividing one's weight (in kilograms) by their height (in meters squared). One is considered to be overweight if their BMI value is greater than 25.0, and obese if their BMI value is greater than 30.0 (2). From the statistics, adiposity was higher in Canadian men, with 62% of men reported as being overweight or obese, while 45% of women reported being overweight or obese (3). This translates to almost fourteen million Canadians overweight or obese. Although the percentage of overweight Canadians has been relatively stable from 2000-2011, the rates of obese individuals have been rising over the same time frame (4). Twells et al. (4) found the percentage of individuals in the normal weight category over time has been steadily decreasing, with increases seen in all three classes of obesity, in particular the highest obesity class (class III). The trend has been seen across the different provinces and territories. There have been differences seen in the trends among Canadian men and women. The rate of obesity from 2007 to 2012 among Canadian males has been stable and shown signs of a declining trend. The prevalence of overweight and obesity among Canadian youths aged 12-17 does not show a significant change between 2005 and 2012. The trends for Canadian females do not indicate the same stabilization. For Canadian females, there has been a steady increase in the prevalence of obesity since 2003 (7).

Body Mass Index - Average Combined Canadian Men and Women
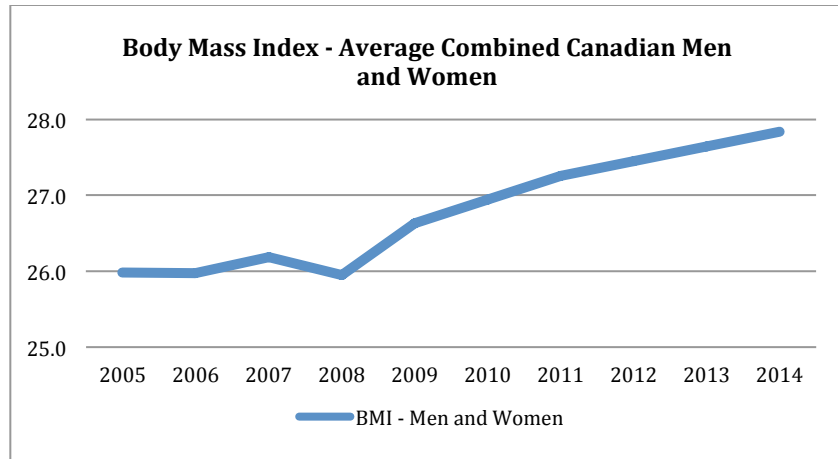
Figure 1: Body Mass Index: Average Combined Canadian Men and Women (108) (109)

Figure 1 highlights the trend seen in the BMI among Canadian men and women over time. Over the past decade, we see the average BMI increasing, while still staying within the range of overweight.

This thesis focuses on adiposity and public policies in the province of British Columbia (BC). Figure 1 depicts the trend of BMI among BC residents from 2001-2011.
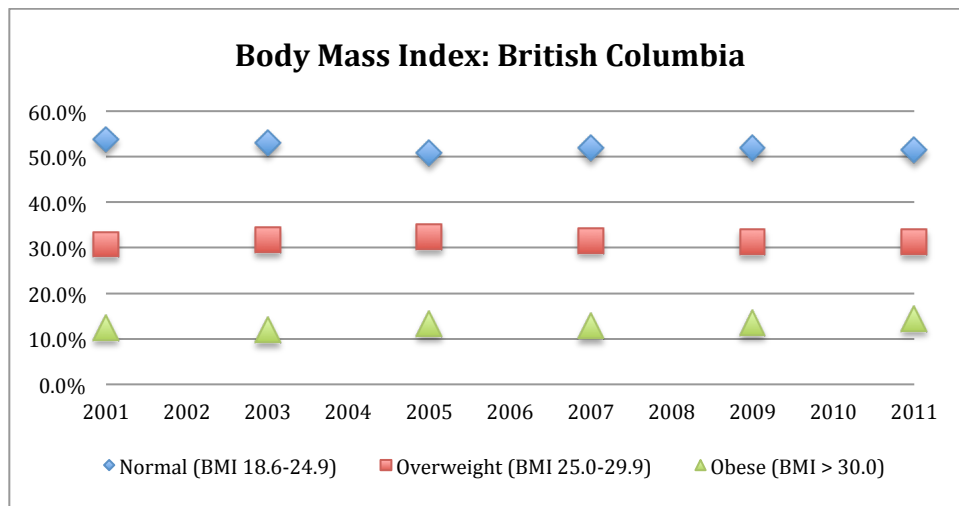
Figure 2: Body Mass Index: British Columbia (1)(3)(5)

While data from the Canadian Community Health Survey (CCHS) 2007/2008 cycle shows that BC residents had the lowest rate obesity in comparison across the provinces, there are still wide differences within the province indicating further room for

improvement (6).   Recent evidence shows there has been no statistically significant change in the rate of overweight among the BC population between 2003 and 2012 (7). Although recent data highlights a slow down or decline in the rates of overweight and obesity among some target groups, the current and future implications of the current state allow for many improvements to be made with regards to the weight of Canadians.

1.2 Impact of Overweight and Obesity

The consequences of obesity can be felt at both an individual and a societal level. This This results in challenges for overweight and obese individuals, as well as health care practitioners and policy makers. Obesity itself increases the risk of many chronic health conditions, including cardiovascular disease, metabolic diseases such as type 2 diabetes, mental health conditions (8) and some forms of cancer including esophageal, gastric, pancreatic, and bowel cancers. The World Health Organization states that after tobacco use, overweight and obesity are the most known avoidable causes of cancer (9). One Canadian study estimated that the proportion of all deaths among adults 20-64 years of age that could be theoretically attributed to overweight and obesity grew from 5.1% in 1985 to 9.3% in 2000 (10). Aside from the detrimental impact obesity has on one's physical health, a review of the evidence conducted by the Provincial Health Services Authority of British Columbia has shown that overweight and obesity impact one's mental well-being (6). For example, the negative attitudes and stereotypes about those who are overweight can lead to both social and employment discrimination, including the potential for lower income, reduced employment opportunities, high job strain, and low co-worker support (12).

2 Methodology

2.1 Analysis of the Obesity Trend

There have been a number of studies attempting to understand the underlying causes of the obesity trend. Although many studies have investigating the myriad of factors, these often focus on only one piece of the bigger picture (10). Some studies have moved past a reductionist approach by taking a comprehensive perspective to understand

the complexity of obesity. At the core of many of these studies is the role of the interaction between biological (e.g. genetics and physiology), behavioural (e.g. physical activity and healthy eating), and socioeconomic factors (e.g. disposable income, norms about foods). Understanding the many interactions between these components is the hallmark of a systems thinking approach. This approach has been used by studies aiming to achieve a comprehensive perspective. Models that integrate social, physiological and economic aspects can provide deeper explanations of the observed dynamics of obesity and suggest policies tailored to specific communities. In order to do so, concepts such as feedback loops and causality need to be addressed (13). Feedback is defined as a circular process of influence in which an action or event is part of a chain of cause and effect that forms a circuit or loop that feeds back on itself (14)

The following section provides an overview of different approaches used to study obesity from a systems perspective. The section outlines work done using conceptual models (e.g., causal loop diagrams), as well as simulation models.

2.1.1 Conceptual models

A Causal Loop Diagram (CLD) is a tool used for diagramming the feedback structure of systems. CLDs are simply maps showing the causal links among variables with arrows from a cause to an effect (15). For an example of a CLD, refer to Figures 4 through 7. (CLDs highlight feedback within a system. CLDs enhance linear and laundry list thinking by introducing circular causality and providing an opportunity for people to externalize their mental models and assumptions. They work to facilitate inference of modes of behaviour by assisting mental simulation of maps (16). Identifying feedback loops from the diagram may help to explain behaviour or to generate insights (17). Understanding the feedback loops at play in the development of obesity is a key area of knowledge that can propel policy makers to identify more successful interventions to combat the obesity problem. By understanding the different feedback loops of a system, policy makers are provided with a wider range of options regarding policy interventions. For example, policy makers may not only focus on weakening loops that produce unwanted behaviour, but can also identify opportunities to strength loops that lead to beneficial behaviour, create new control mechanisms that impact negative loops, or work

to transform a loop producing unwanted behaviour into one that can produce beneficial behaviour (18). Although causal loops can provide great insight into a systemic problem, they are notoriously unreliable tools for behavioral inference (16). The mechanisms one emphasizes in an untested causal-loop diagram may or may not be the ones the client really ought to be most concerned about. In other words, only using a map is limited and possibly misleading: simulation or formal models are needed to test the map (16). Causal-loop diagrams have long been used in standard system dynamics practice for two purposes connected with simulation modeling. They were initially employed after simulation, to summarize and communicate model based feedback insights (16).

The Foresight Obesity Map developed in the United Kingdom is a commonly used example for a causal loop diagram of the obesity system.
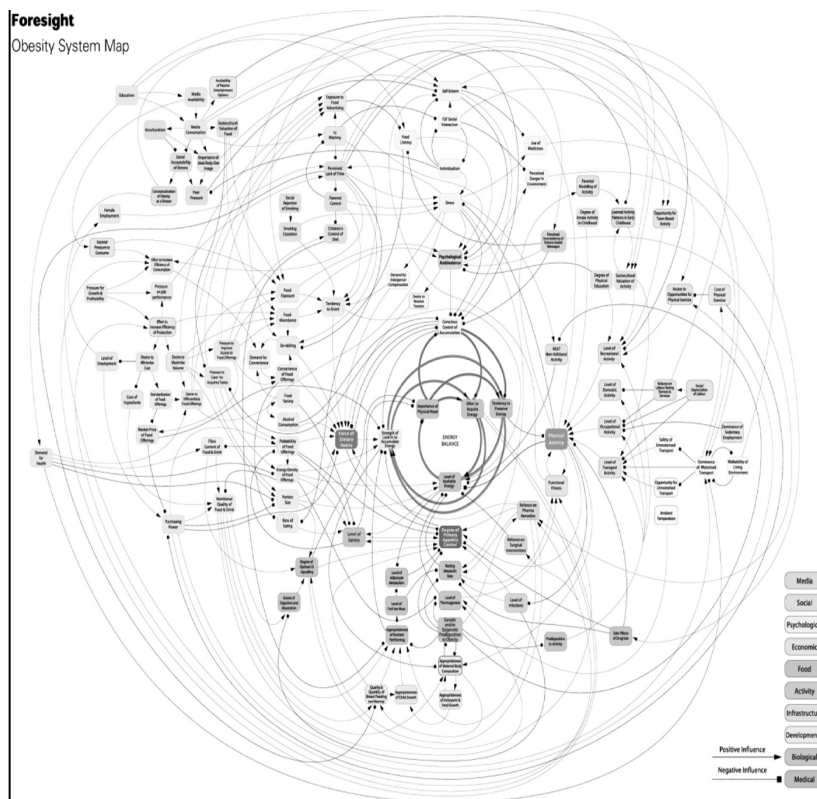
Figure 3: Foresight Obesity Map. For a higher quality rendering of the map, we refer the reader to *(19)*.

The map was created with the goal to help understand the complex system structure of obesity and to be used as a tool for aiding policy makers in testing possible policy options in respond to obesity (19). The map itself identified the broad range of

factors that influence obesity. A separate analysis of the Foresight map identified four broad sectors influencing obesity - physiological factors, eating habits, activity levels and psychosocial influences (20). Within each of these main sectors, a key determinant of vulnerability was identified. These vulnerability determinants included primary appetite control in the brain, the force of dietary habits keeping individuals from adopting healthier alternatives, physical activity level, and the psychological ambivalence experienced by individuals in making lifestyle choices. (19). The variables in the map are interrelated through more than three hundred connections and more than one hundred feedback loops (14).

  With the boundaries of the obesity system delineated by the Foresight map, the problem of obesity can be said to emerge from the adaptive responses to the interaction between the system and policies (food, physical activity, and social environments) which shape the environment in which the system operates (20). Although the map successfully identifies important linkages between factors influencing obesity, it does not provide support for heterogeneity (21). Similar mapping approaches have looked at factors influencing obesity. In their report "Connecting physical and mental well-being in relation with overweight and obesity" the Provincial Health Services Authority of British Columbia (PHSA) created a conceptual map that illustrated how a diverse range of factors contribute to and resulting from obesity are interrelated (6) The map seen in Figure 4, framed these factors not only in the perspective of obesity, but also in a more holistic approach by framing the interactions in terms of physical and mental wellbeing. The identification of multiple feedback loops involved in obesity and well-being work to aid decision makers in designing interventions aimed at reducing obesity (6).
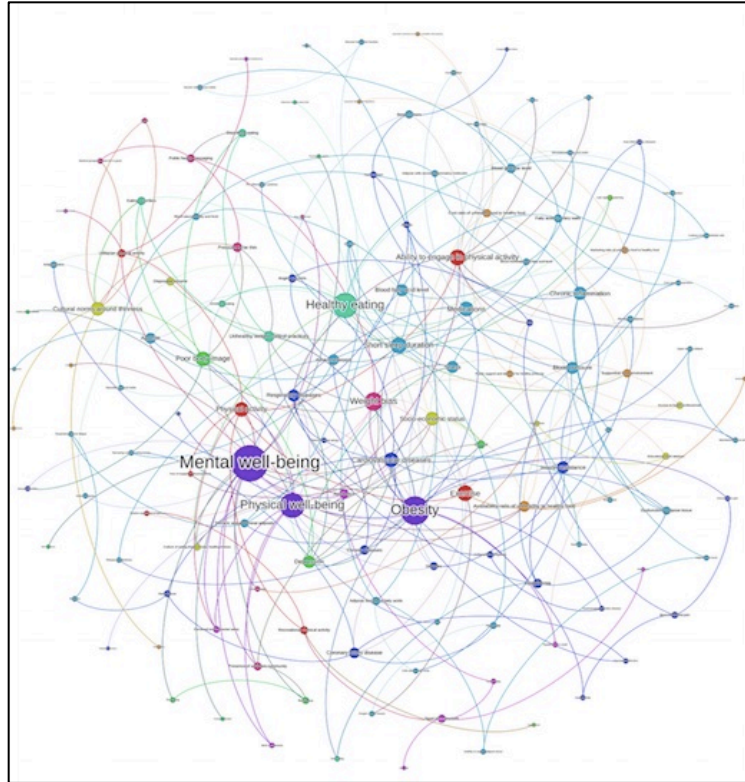
Figure 4: Causal Loop Diagram by PHSA. For a higher quality rendering of the map, we refer the reader to (6).

2.1.2 Simulation modeling approaches

A number of studies have incorporated a quantification aspect to their analysis of the development of obesity through the use of simulation models. Also known as a computational model, a simulation model is one in which a model is driven by suitable inputs and produces corresponding outputs (22). Simulation in general is a third way of doing science. Like deduction, it starts with a set of explicit assumptions. But unlike deduction, it does not prove theorems. Instead, a simulation generates data that can be analyzed inductively. Unlike typical induction, however, the simulated data comes from a rigorously specified set of rules rather than direct measurement of the real world. These rules are expressed in the form of equations used to describe particular concepts (22) for example physical activity behaviours. There is a strong need to create such tools for practitioners and policy makers in dealing with the complexities they encounter within obese patients and an obese (6). As John Sterman has stated that without modeling, we may believe we are learning to think holistically, when in reality we are actually learning

to jump to conclusions. (23) Conceptual models cannot study what-if scenarios, which limits their ability to foresee what the most relevant or sensitive factors for achieving a desired result. In contrast, simulation models provide a tool for formally testing a dynamic hypothesis about a particular problematic behaviour in a system and determining its adequacy. (16). Furthermore, simulation models provide a medium to add discipline to the policy dialogue as well as demonstrating trade offs and suggesting efficiency opportunities for improving a system (24).

Apart from offering the opportunity to study what-if scenarios and leverage points for change in a system, simulation modeling provides a formal tool for testing these leverage points. As leverage points are often not intuitive or are attempted to be improved upon in a counterintuitive manner (25) a formalized tool such as a simulation model can help test one's intuition in a safe environment. Simulation models can quantify and forecast the effects of public policies on obesity, health, and other outcomes. Simulation models can show the successes and failures of past policies, as well as predicting the consequences of selected policy proposals before their implementation. To develop a comprehensive approach, simulation models ultimately need to simultaneously consider multiple policies, how the effect of a policy depends on the manner in which it is implemented and the other policies in effect, how the effects vary by sociodemographic group and how the effects vary over time (13). Simulation models can integrate knowledge from many fields, which in the case of obesity is key to understanding the big picture of the system influencing one's body weight (13).

2.1.3 Simulation models in obesity research

The use of simulation models for policy development within the obesity field is in its early stage of development, however simulation models have been used in other health care fields, ranging from chronic disease management, health care capacity planning, and within the pharmaceutical industry (26). Some studies have created simulations focusing on body weight and obesity. A study conducted by Giabbanelli applied a modeling approach to understanding the contribution of social norms to weight. The model created captured how social norms regarding food and physical activity impact an individual's weight (27). The results of the study suggested the social environment plays an important

role in one's weight, however this environment depends on the connections of the individuals within that environment. In this model, influences were exerted continuously and were cumulative, causing changes only when a threshold quantity was received. This exhibits non-linear dynamics that were advocated to improve the realism of models. Non-linearity is an important concept related to system change, as it is often misunderstood as change is commonly assumed to be gradual and linear (28). This can be the case is some systems across some periods of time, however in many systems in nature, change is characterized by periods of turbulence and instability, with dramatic changes or growth spurts (28).

Studies completed by Edwards et al. and Bahr et al. have also investigated the relationships of social networks and obesity using a simulation model approach. The results obtained by Edwards show that social capital and poverty are strongly associated with childhood obesity (104) while Bahr's work found that for a wide variety of conditions, individuals with similar BMIs were found to cluster into groups, and social forces drove these groups towards increasing obesity (105). Furthermore, simulation models have been used to understand obesity not only from a population perspective, but also from an individual perspective. Models have been developed that show the dynamics of energy regulation at the individual and biological level in order to understand issues such as weight cycling (29).

2.2 System dynamics

System Dynamics (SD) is one specific branch of simulation modeling. It applies to dynamic problems arising in complex social, managerial, economic, or ecological systems — literally any dynamic systems characterized by interdependence, mutual interaction, information feedback, and circular causality (30).

2.2.1 Applications of system dynamics and obesity

There have been a small number of applications of this approach to obesity and weight. Rahmandad applied system dynamics in a model that replicates key trends in human growth, including changes in energy requirements from birth to old ages and short and long-term dynamics of body weight and composition. (31). Abdel-Hamid applied a

system dynamics approach in a similar fashion to Rahmandad, as his research focused on modeling and gaining insight into the physiology related to weight gain and loss (106). A simulation model was developed that integrated nutrition, metabolism, hormonal regulation, body composition, and physical activity (32). Homer et al. (32) developed a system dynamics simulation model to understand trends in obesity in the USA. Data on population body weight from 1971-2002 were combined with information from nutritional science and demography into a single analytic environment for conducting simulated policy experiment. Hovmand and White also applied system dynamics using a population approach in their work investigating the role of social determinants in the development of childhood obesity in St. Louis, Missouri (34). Fallah-Fini et al. connected the micro-level dynamics associated with elements in a population with the macro-level population distribution while recreating the pattern of development of the BMI of American women over time (35).

2.2.2 Benefits of approach

Obesity is a complex, not simply a complicated problem, there are many factors contribute to the problem. As these problems often relate to each other in nonlinear fashions, are subject to time delays, and change over time (13), the application of system dynamics lends itself to understanding these characteristics with respect to obesity. System dynamics modeling can help explore the complex multilevel social influences of obesity, identify potential gaps in research, and plausible intervention levers with policy implications by analyzing outcome patterns (29). As system dynamics allows one to test combinations of prevention and treatment intervention impact directed towards overweight and obesity individuals, it is a useful tool for policy makers as it can enhance their ability to understand the combination of strategies with potential for greatest impact. (29). Few population-level obesity prevention and management interventions have been evaluated from a systems perspective (10). A system dynamics model can serve to fill this evaluation gap. Aside from a public policy perspective, using system dynamics can provide useful insight into helping not only policy makers, but also practitioners, understand the complexities of obesity. As many practitioners, in particular physicians, have suffered from insufficient guidance on understanding and managing obesity (36),

there is a need to improve the understanding of those who are dealing with obesity at the frontlines. There are many types of simulation models that are capable of projecting future trends in obesity prevalence, however the benefit of a dynamic simulation model, (e.g. the type of model a system dynamics methodology creates) enables a more sophisticated analysis by incorporating changing population parameters over time, such as changing socio-demographic characteristics of a population (13). The simulation ability of system dynamics can demonstrate the need for public health policy by quantifying and forecasting the effects of obesity on health and other outcomes (13). As simulation models can highlight the successes and failures of past policy proposals prior to their implementation (13), the simulation aspect of system dynamics work to aid policy makers in learning from their past and preventing the implementation of sub-optimal policies.

The application of system dynamics with the obesity field has been primarily focused on understanding the role of physiology in obesity development or through understanding how a particular set of factors has influenced the development of obesity over a particular time frame. Within the realm of all simulation models, most models focus on one or two links in the process of obesity development, from changes in public policy to the health implications of obesity (13). Ferencik and Soderquist however applied system dynamics methodology that focused on public policy, rather than physiology. They used the system dynamics methodology as a tool to help aid policy makers in building systems thinking capacity with regards to policies on childhood obesity (106).

The purpose of this thesis is to go beyond the current SD work and apply the methodology to analyze the problem from a holistic perspective – looking not only at the links between one or two factors, but to see how four major sectors – physiology, physical activity, the food environment, and mental well-being, combine to play a role in influencing's an individual's weight over time. In doing so, the SD model can better support both policymakers and health practitioners in gaining a better understanding of the feedback processes influencing one's weight and the non-linear causal relationships that exist between factors and within each sector   By developing a tool to improve understanding of the complex systems driving weight dynamics, it can enable decision

makers to better support individuals in achieving a healthy weight.

2.3 Applied Methodology

As the aim of thesis was to develop a simulation model to see 'how' the interactions between a variety of factors over time could lead to changes in weight and well-being, rather than to investigate 'what' the factor are, it was decided to use a previously created map outlining the different factors and their connections that are at play within a weight and well-being system. The starting point for three of the four sector structures (mental well-being, physical activity, food environment) of the simulation model was the CLD created by the research team at the Provincial Health Services Authority of BC. The fourth sector (physiology) primarily drew on the work of Hall (50). The process used to translate the CLD into a SD simulation model was adapted from the modeling process developed by Sterman. The process designed by Sterman (15) was as follows:

Modeling Step	Key Actions
1. Problem articulation	• Theme selection • Identification of key variables • Time horizon • Dynamic problem definition (reference mode)
2. Formulation of dynamic hypothesis	• Initial hypothesis generation • System mapping
3. Formulation of simulation model	• Specification of structure and decision rules • Estimation of parameters and initial conditions
4. Testing	• Comparison to reference mode • Sensitivity tests • Model validation
5. Policy design and evaluation	• Scenario testing • Sensitivity analysis • Interactions of policies

Table 1: Modeling process

As this thesis is building upon the previously completed work of the PHSA, the nature of the relationships presented within the CLD were not analyzed themselves. The initial goal of the translation from CLD to stock and flow model was to attempt to include all variables from the CLD into the stock and flow model. Due to the nature of the variables (the majority of variables being soft variables) and the available data on such variables, the outcome goal of the model needed to be revised during the modeling process. This resulted in the overall goal being to include representation from four major sectors. Factors that were identified to be central to a particular sector (i.e. incorporated within feedback loops) where prioritized to be added to the stock and flow model. Furthermore, different levels of aggregation resulted in the inclusion of some relationships that were not portrayed as direct relationships in the CLD. The limited data for some variables and relationships required that some variables be modeled at different aggregation levels. For example, the food environment sector was represented on a highly aggregate level to include income and ease of purchase healthy foods. Within the CLD created by the PHSA, this is not portrayed as a direct relationship.

There were some deviations from the modeling process as outlined by Sterman. As the model created was an exploratory model, rather than an explanatory model, the outcome goal of the model was not to produce a behaviour that matched a specific reference mode. Instead, the pattern seen in the increase of BMI over time serves as a general reference behavior pattern that the model attempts to match. Secondly, the formulation of the dynamic hypothesis and system mapping was previously completed through the development of the CLD. Third, policy design and evaluation was not completed within the thesis work. The emphasis was on developing a model using current evidence and knowledge from experts, such that it can be used in future studies to identify cost-effective interventions; consequently, economic analyses are beyond the scope of the present thesis.

3 Model Description

3.1 Sector Conceptualization

3.1.1 Overview

The overall model investigates how interactions between the four major areas (physiology, physical activity, mental well-being, and food environment) influence one's weight and well-being over time. The causal loop diagram in Figure 5 provides an overview of the feedback loops at play within the model.
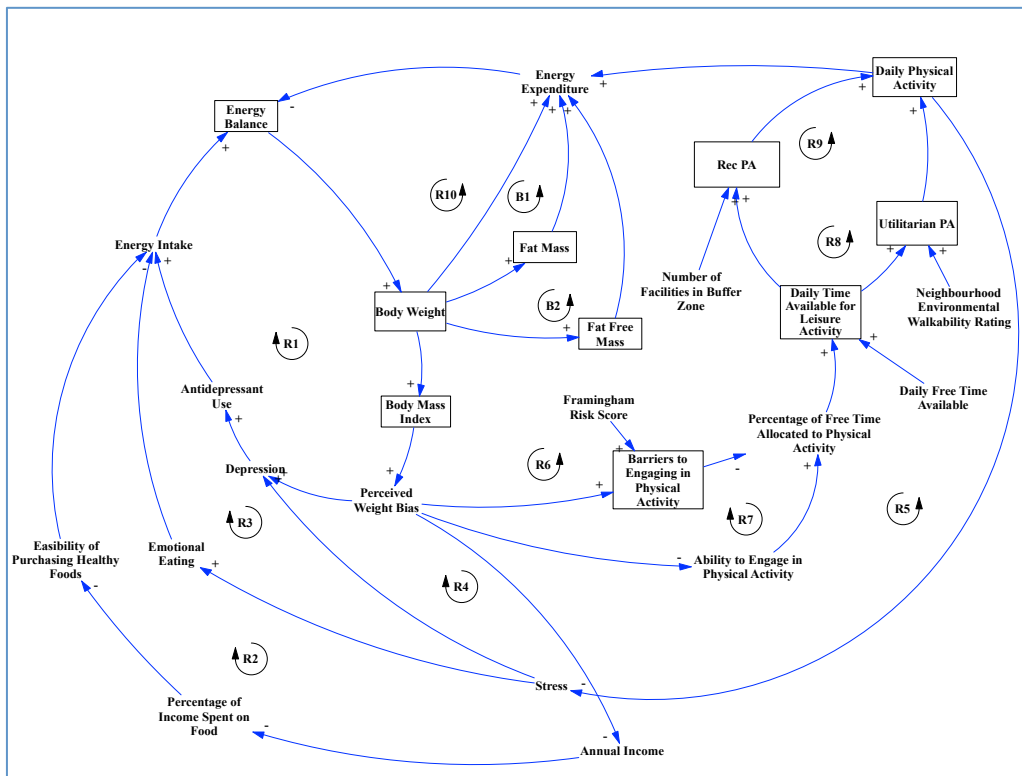
Figure 5: Causal Loop Diagram of Simulation Model

The model is governed by ten reinforcing loops and two balancing loops. Loops R1, R2, R3, R4, and R5 influence the energy intake of an individual, while loops R6, R7, R8, R9, and R10 work on influencing the energy expenditure of an individual. Loops B1 and B2 work on the energy expenditure. The following discussion provides more in-depth information on each sector. First, an overview of the conceptualization of each sector is

provided with key concepts outlined. Second, information is provided regarding the validation of each variable and parameter within each sector. Third, any calibrations that were needed for a variable or parameter are outlined.

3.1.2 Physiology Sector

At the core of the overall model structure lays the physiology sector. The underlying concept of the model is that a change in body weight results from an imbalance between the intake of energy from food and the energy expended to maintain life and perform physical work (37). The physiology model structure used was adapted from a previous version used by Chow and Hall (37) with further adaptations incorporated based upon revised works on the Chow and Hall model completed by Rahmandad (31) and Fallah-Fini (35). Within the physiology model, the three major pieces involved in weight dynamics are the energy intake, energy expenditure, and energy partitioning.

The physiology model acts as the focal point for the model as it captures the overall dynamics of the larger system at play through two stocks - individual's fat mass and fat free mass. Fat mass can be defined as any body lipid material that would be soluble and extractable in ether, while fat free mass refers to body mass that are not considered fat mass, such as muscle, bone, and water (38). The changes seen in the two stocks result from a change in one's daily energy balance.   The daily energy balance is the difference between one's energy intake and energy expenditure. The energy intake refers to the daily kilocalories consumed by an individual. This flow is governed by the energy expenditure and from other components (mental well-being and food consumption).

The physiology model can be described as a black box model in which there are only two points where the boundaries of the external forces (those outside the physiology sector) and the physiology model meet. These two points of interconnection are the two flows driving the daily energy balance - the energy intake flow and the energy expenditure flow. Any change in the factors influencing either of these flows will ultimately alter the daily energy balance, leading to either weight gain (and increase in fat and fat free mass) or weight loss (a decrease in fat mass and fat free mass). The allocation

of the energy imbalance to either fat mass or fat free mass is determined by an energy partitioning factor. The physiology sub-system is schematized in Figure 6.
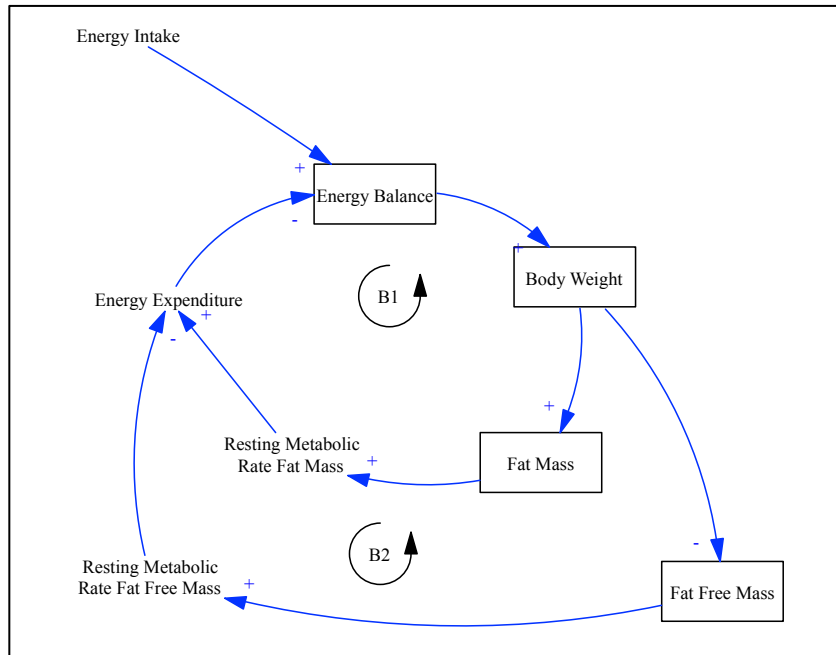
Figure 6: Causal loop diagram of physiology sector

The model is governed by two balancing loops that work towards achieving no energy imbalance, either by altering the fat or fat free mass in the body. Resting metabolic rate refers to the average energy metabolism of a person resting in a comfortable environment, not engaged in any physical activity (110). Any change in either of these variables results in a change in energy expenditure through a change in the resting metabolic rate. For example, a step increase in energy intake would not result in an infinite weight gain. Instead, this would result in an increase in both fat mass and fat free mass, thus increasing each mass's resting metabolic rate, leading to an increase in energy expenditure to a level that matches that of the energy intake. This physiology model allows for a comprehensive approach to capturing weight dynamics as it makes explicit the type of body mass composing body weight - fat mass and fat free mass. In doing so, the model is able to account for differences in their metabolic rates and growth requirements. This explicit distinction paints a more realistic picture of the process of one's weight change, as the process is not solely dependent on energy intake versus

energy expenditure, but also is dependent on body composition (37). Furthermore, this formulation of weight provides a more realistic depiction of weight than in other models where weight is simplified to a single component as in the model by Giabbanelli et al. (27).

3.1.3 Physical activity sector

The physical activity sector reflects how both the built environment and individual characteristics play a role in determining the volume of physical activity one engages in on a daily basis. The physical activity sub-system is schematized in Figure 7.
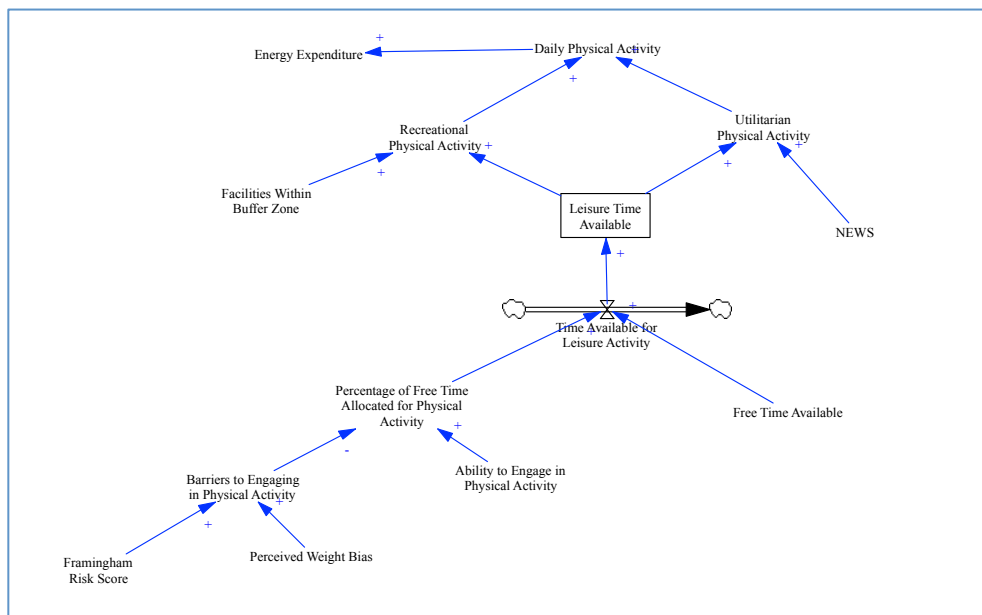
Figure 7: Causal loop diagram of physical activity sector

The initial driver for the physical activity sector stems from the variable Free Time Available. This represents the amount of time Canadians can dedicate towards leisure time activity on a daily basis. The time that they do dedicate towards leisure time activities is influenced by one's ability to engage in physical activity and one's barriers to physical activity. In the model, one's perceived weight bias and physiological limitations (capture here by the Framingham risk score) act as barriers to physical activity. The Framingham Risk score is a risk assessment tool that uses is used to predict a person's

chance of having a heart attack in the next 10 years (39). The stock "Time Available for Leisure Activity" represents the time per day that an individual allocates towards active leisure activities. Based upon factors in their built environment, this determines whether the time available is used for physical leisure (physical activity), social leisure (activities where the primary focus is socializing with family and friends), or cognitive leisure (where the focus is on hobbies, games, and other mentally stimulating activities) (52). The flow Daily Recreational Physical Activity represents the fraction of leisure time allocated towards recreational physical activity. Recreational physical activity is defined as any physical activities that individuals engage in for enjoyment or pleasure (6), rather than because they are necessary to accomplish a task (e.g. cycling to get groceries). These activities may also be known as leisure-time physical activities (6). These activities are often described as part of a larger category of activities called leisure time activities (40). The flow is governed by the effect of the number of recreational facilities within an individual's buffer zone. The flow Daily Utilitarian Physical Activity represents the fraction of leisure time allocated towards utilitarian physical activity. Daily utilitarian physical activity refers to those activities that serve the practical purpose of transporting someone from one place to another. This includes active transport, which refers to any form of human-powered transportation such as opting to cycle to a place rather than drive. Examples of facilities necessary for utilitarian physical activity include sidewalks, trails, bicycle lanes, and amenities such as stores, community centers, libraries, and restaurants (41). This is summarized by the Neighbourhood Environment Walkability Score (NEWS, which measures residents' perceptions of the environmental attributes of their local area (42). Specifically, NEWS was used as a questionnaire to assess residents' perceptions of neighborhood characteristics related to a higher frequency of walking and cycling trips (42).

Both recreational physical activity and utilitarian physical activity combine to form one's daily physical activity level. There are two main outputs of the physical activity sector. The first is the daily physical activity, which influences the physiology model via energy expenditure. In order to translate one's daily physical activity into a coefficient value that can be used in one's energy expenditure equation, the daily physical

activity volume was translated first into a physical activity level (PAL). The PAL is the ratio of total energy expenditure to basal energy expenditure (43). One's PAL is a measure of both volume and intensity of activity. As one's PAL is calculated, it has an effect on the physical activity coefficient of the energy expenditure. The second output of the physical activity sector can be seen through the effect of one's PAL on stress.

3.1.4 Mental well-being sector

The mental well-being sector of the model is the most connected sector of the model, creating feedback loops involving all other sectors. A CLD of the sector can be found in Figure 8.
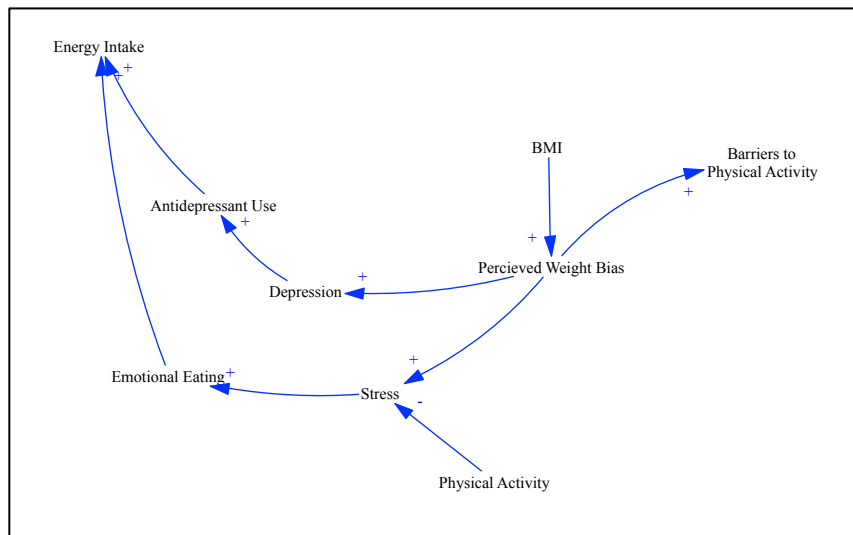
Figure 8: Causal loop diagram of mental well-being sector

The mental well-being sector looks at how one's mental well-being influences one's energy intake, their annual income and ability to purchase healthy food, as well as their physical activity. At the heart of the mental well-being sector are two common challenges to well-being: depression and stress. Depression can be defined as a common mental disorder characterized by sadness, loss of interest or pleasure, feelings of guilt or low self-worth, disturbed sleep or appetite, feelings of tiredness and poor concentration (44). Stress can be defined as the brain's response to any demand. Many things can trigger this response, including change. Changes can be positive or negative, as well as

real or perceived (45). Both depression and stress are driven in the model by Perceived Weight Bias. Weight Bias or stigma can be defined as the negative attitudes towards a person because he or she is overweight or obese. For example, these can include the stereotype that an obese person is lazy or lacking willpower to lose weight (12). Weight bias is caused by a general belief that obesity is entirely under ones control (e.g. inadequate self-discipline, insufficient willpower) and that it is a very undesirable trait (46). Weight bias is defined as perceived weight bias as this enables the model to include an individual perspective on the variable. The perceived weight bias is influenced by one's body weight. Perceived weight bias drives both stress and depression.

In this sector, both stress and depression impact energy intake. One's level of depression impacts their use of antidepressants, which in turn influences one's energy intake level. One's level of stress also effects energy intake by influencing one's level of engagement in emotional eating behaviors. Stress is also impacted by one's level of physical activity.

3.1.5 Food environment sector

The food environment sector portrays the impact of one's ability to purchase healthy foods on his or her energy intake. Just as in the mental well-being sector, one's perceived weight bias is the driver for this sector. One's perceived weight bias on an impact on one's potential annual income. As one's potential annual income is decreased, this has the potential to reduce their ability to purchase healthy foods. This effect depends on the ratio between the cost of healthy food and one's Actual Annual Income. Depending on how able one is to purchase healthy foods, this will impact their energy intake in an indirect manner. Figure 9 portrays the causal loop diagram of the food environment sector.
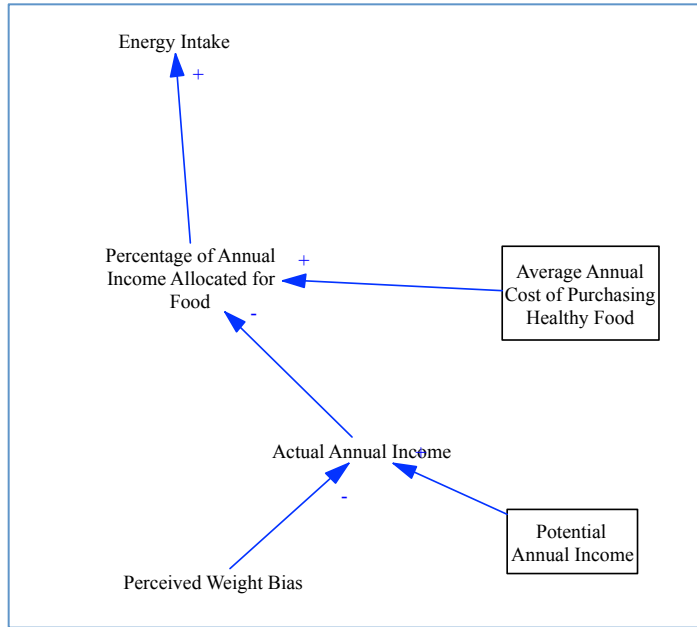
Figure 9: Causal loop diagram of food environment sector

3.2 Variables and Parameters

3.2.1 Physiology Sector

Energy Intake

The inflow of the energy balance stock is the energy intake. In the model, energy intake is determined by the multiplication of the effect of energy intake and energy expenditure. At any point in time, the energy intake is impacted in equal proportions by three effects the ease of purchasing healthy foods, emotional eating, and antidepressants.

Each of the three effects is driven by a target value. For example, the variable Actual Effect of Emotional Eating on Energy Intake is driven by a Target Effect of Emotional Eating on Energy Intake. The target variables provide the true effect of a particular ratio, while the Actual Effect variable is a smooth function that the target value. A smooth function was applied here as it represents a delay in behavior change due to time required to gather and process information. For example, a change in the ease of purchasing healthy food would not instantaneous change based upon a change in the Percentage of Annual Income Allocated for Food Ratio. It would take time to perceive

the change and to alter behavior. Such delays in the model are represented by a first order smooth function with a delay time of six months.

Energy Expenditure

The outflow of the energy balance stock is the energy expenditure. The energy expenditure is governed by equation 1.

Equation 1:

$Energy\ Expenditure = K + (\gamma_{FFM} * FFM) + (\gamma_F * FM) + \delta BW + \beta \Delta EI + (\eta F * dFM/dt) + (\eta FFM * dFFM/dt)$

Constant	Name	Definition	Value	Unit of Measure	Calculated or Assumed Value	Source
K	Constant	The energy expenditure required for brain function.	370.21	Kcal/day	Assumed	(48)
γ_{FFM}	Resting metabolic rate of fat free mass	The energy cost of maintaining metabolic homeostasis, nerve and muscle tone and circulation and breathing of fat free mass	22	Kcal/kg/day	Assumed	(48), (49)
γ_{FM}	Resting metabolic rate of fat mas	The energy cost of maintaining metabolic homeostasis, nerve and muscle tone and circulation and breathing of fat mass	3.6	Kcal/kg/day	Assumed	(48), (49)

δ	Physical activity coefficient	The amount of energy expended for daily physical activity	7	Kcal/kg/day	Assumed	(48)
β	Adaptive Thermogenesis Parameter	The amount of energy expended during a diet perturbation	0.24	Unitless	Assumed	(48)
ηF	Energy deposit for fat mas	The energy required to deposit additional fat mass	180	Kcal/kg	Assumed	(48)
ηFFM	Energy deposit for fat free mass	The energy required to deposit additional at free mass	230	Kcal/kg	Assumed	(48)
dt	Delta time	How frequently calculations in the simulation model are applied during each unit of time.	1	Day	Assumed	N/A

Table 2: Constants for Equation 1

Table 3 describes the parameters composing the energy expenditure equation. All values within the table are calculated.

Variable	Name	Definition	Initial Value	Unit of Measure
FM	Fat mass	Any body lipid material that would be soluble and extractable in ether	56.03	Kg
FFM	Fat free mass	Any body mass that are not considered fat mass, including water, protein, and minerals	14.69	Kg
BW	Body Weight	The total weight of an individual (FFM + FM)	70.27	Kg

ΔEI	Change in energy intake	The impact of changes in energy intake over time on energy expenditure.	0	Kcal/day
dFM	Change in fat mass	The change in fat mass over the period dt	0	Kg/day
$dFFM$	Change in fat free mass	The change in fat free mass over the period dt	0	Kg/day

Table 3: Parameter Description of Energy Expenditure Equation

The parameters γ_{FM} and γ_{FFM} refer to the regression coefficients that relate the resting metabolic rate of fat free mass versus fat mass 48). Hall (48) determined the mean value for γ_{FFM} to be 22 +/- 4 kcal/kg/day, while the mean value for γ_{FM} was 3.6 +/- 2 kcal/kg/day. The mean values for both regression coefficients were used in the model. The physical activity coefficient, δ, was determined by Hall (48) to be proportional to an individual's body weight, and the mean value was determined to be 7 +/- 4kcal/kg/day. A value of 7 kcal/kg/day was used in the model. Hall, Sacks, and Chandramohan (50) determined this value based upon the assumption of a sedentary physical activity level (PAL).

The thermic effect of food, also known as dietary induced thermogenesis, is the amount of energy needed to process the food intake. This is captured through the parameter β, which adapts the energy needed to process food when the amount of food changes (48). A mean value of 0.24 +/- 0.1 was calculated and a value of 0.24 used in the model (48) the change in energy intake, ΔEI, takes into account the impact of changes in energy intake over time on energy expenditure. The parameter is rooted in the understanding that over time, one's body composition alters the energy intake required to maintain a zero energy balance (48). This parameter is specified by Equation 2.

Equation 2:

$$\Delta EI \cong \left(\frac{dBW}{dt}\right) * \frac{9100 kcal}{kg} + (\overline{BW}\ mean - \overline{BW}\ _0) * 22 kcal/kg/da\ .$$

The first term, $\left(\frac{dBW}{dt}\right) * \frac{9100 kcal}{kg}$ accounts for a change in body weight on a daily basis and adjusts for an adequate energy intake to maintain energy balance, while the second

term, $(\overline{BW}\ mean - \overline{BW}_0) * 22 kcal/kg/day.$ accounts for an adapting baseline energy expenditure over time, depending on changes in body weight over time (48). Finally, one's energy expenditure takes into account the energy required to deposit additional fat and fat free mass, ηF and ηFFM respectively. The mean energy cost for depositing fat mass is 180 +/- 20kcal/kg and for fat free mass to be 230 +/- 100 kcal/kg (48). Both mean values are used in the model. The total cost for depositing new fat or fat free mass is determined by the rate of which new fat mass or fat free mass is created (dFM/dt and dFF/dt respectively) (48).

Energy Partitioning Factor

The energy partition factor determines the rate of allocation of the daily energy balance to become either fat mass or fat free mass. It is assumed that the partitioning factor is not a fixed percentage, as studies have shown the percentage of body fat lost depends on the body composition (37). The partitioning factor for adults is defined in Equation 3.

Equation 3:

Energy Partitioning Factor
$$= Forbes\ body\ composition\ parameter/(Forbes\ body\ composition\ parameter + Fat_{Mass})$$

The partition factor is a function of the Forbes Body Composition and the current fat mass. The Forbes body composition parameter is defined in Equation 4.

Equation 4:
$$p = C/(C + F)\ with\ C = 10.4\ kg \times \rho_L/\rho_F$$

This parameter describes how body composition changes as a function of the initial body fat mass (48). The factor is calculated by multiplying the energy densities for changes in fat (ρ_F = 9400 kcal/kg/day) and fat free mass (ρ_L = 1800 kcal/kg) by a constant of 10.4 kg. Overall, the energy partitioning function allows for a nonlinear

model of body composition changes (48). As the partitioning factor determines the allocation of the energy imbalance towards either fat mass or fat free mass, the energy densities for fat mass and fat free mass determined the actual volume of change in the fat mass and fat free mass respectively. The flow change in fat mass is governed by the partitioning factor, the size of the energy imbalance, and the energy density for fat mass (the volume of energy needed to add or remove one kilogram of fat mass). The flow change in fat free mass is governed by the same three factors. It should be noted that these flow changes do not take into account physical activity, which has the potential to alter the balance of fat mass and fat free mass growth. Changes in fat mass and fat free mass will lead to two effects. First, they have a direct effect on the body weight of the individual. Second, a change in either mass will lead to a change in resting metabolic rates. This change in resting metabolic rate will in turn change the daily energy expenditure of the individual, as a higher fat mass and fat free mass will expend more energy on a day to day basis.

3.2.2 Physical Activity Sector

Time Allocation

The driver of the physical activity sector is one's Free Time Available. The value of free time available is 5.5 hours per day. A study indicated that in 2005 British Columbia residents allocated 336 minutes (5.5 hours) of their day to free time (51). Free time was composed of four activities: socializing, passive leisure activities, sporting and entertainment events, and active leisure activities. Active leisure activities consisted of social leisure, cognitive leisure, and physical leisure (52). For the purpose of this thesis, the activity of interest is physical leisure, as this type of activity would result in an activity level of moderate to vigorous activity. The report (52) indicates that an average of 1.1 hours was spent in active leisure activities. Consequently, the value of Time Available for Leisure Activity (Equation 4) was initialized to 1.1 hours. The equation governing the flow of Time Available for Leisure Activity consists of the total free time available multiplied by the fraction allocated to physical activity. The Percentage of Free

Time Allocated for Physical Activity is calculated from the addition of two effects: one's barriers of engaging in physical activity and one's ability to engage in physical activity. For modeling purposes, it was assumed that each of these factors influencing the variable equally (e.g. the weighing factor for each variable is 0.5).

Barriers to Engaging in Physical Activity

The initial value for the stock Barriers to Engaging in Physical Activity level is 0.2. The initial value was selected to represent a low impact of barriers on one's engagement in physical activity. Using a scale of 0-1, with 1 indicating the maximum barrier to physical activity and 0 indicating no barrier to physical activity, a value of 0.2 was selected as an arbitrary value to represent the prototype individual's barrier level. This 0.2 was selected as it represents a low level of barriers to physical activity. As the individual has a BMI within the normal range, it is assumed the impact of weight bias at the initial time of the simulation is minimal. As well, based upon the prototype's BMI it was assumed that their Framingham risk score would also be low (assuming the individual is of good health). This value also represents the normal value of barriers to engaging in physical activity, thus providing a value of 1 for the variable Barrier of Engaging in Physical Activity Ratio. The effect of barriers to engaging in physical activity on Percentage of Free Time Allocated for Physical Activity is represented through a graphical function. The graphical function is an s-shaped curve with the limits of 0-5, as the maximum ratio would be a value of 5 (the initial normal value of 0.2 dividing into the maximum effects influencing Barriers to Engaging in Physical Activity, a value of 1). The s-shaped curve was selected based upon the assumption that any change near the low or high ends (in comparison to the normal effect) result in minimal changes in one's allocation of their free time towards physical activity. There is a lack of current evidence that has investigated what the nature of this curve would be, as well as the upper and lower values. This range of possible effects that this curve entails also represents the range of responses gathered by Giabbanelli in an interview with subject matter experts (53). When asked about the relationship between the effect of fear of engaging in physical activity and it's impact on one's actual physical activity level, three

out of four experts responded medium strength and one responded very weak. The s-shape nature of the curve allows for the relationship between one's barriers to physical activity and physical activity to produce a weak effect (i.e. at the lower end of the curve) and as well a medium effect (near the middle of the curve). In the CLD created by PHSA, the variable Barriers to Physical Activity is represented by the variable "Fear of Engaging in Physical Activity."

Framingham Risk Score

The Framingham Risk Score represents the variable Cardiovascular Diseases in the PHSA CLD. The initial value of one's Framingham Risk Score was selected to be 1 due to the low percentage of British Columbia residents suffering from CVD (3.9% in 2007-2008) (55). The theory behind cardiovascular disease as a barrier to engaging in physical activity stems from the fact that one's cardiovascular condition can limit one's physical abilities to engage in physical activity, and may also in some subjects create anxiety and fear of bringing forth another cardiac incident.   Due to difficulties in operationalizing cardiovascular disease for modeling purposes, the risk score was selected as a proxy variable to represent the concept.

The effect of one's Framingham Risk score on one's fear of engaging in physical activity is represented by the graphical function "Effect of Framingham Risk Score on Barriers of Engaging in PA." Overall, there is a lack of current evidence that has investigated that would determine what the shape of the graphical function would be, as well as what the lower and upper limits of the curve would be. Due to this literature gap, three reference sources were consulted with in order to build the graphical function. First, four expert interviewed by Giabbanelli provided insight on the strength of the relationship between CVD and one's fear of engaging in physical activity. The experts' responses were strong, strong, medium, and non-existent (53). The spectrum of results provided lent itself to using an s-shaped curve to represent such a relationship. Secondly, a study conducted by Kocjan and Knapik (55) found moderate intensity of fear of movement (kinesiophobia) in patients undergoing cardiac rehabilitation, although the authors concluded that one does not necessarily need to have a cardiac incident in order

to experience kinisiophobia, rather the predisposition to kinesiophobia is individually determined (55). Based upon these two sources, it was determined that the nature of the curve should be able to represent provide a range of effects based upon different Framingham Risk scores.

Ability to Engage in Physical Activity

The initial ratio of Ability to Engage in Physical Activity was calibrated to provide a value of 1, indicating the Normal Ability (value of 1) is equal to that of the current value. In the PHSA CLD, one's ability to engage in physical activity is impacted by eight factors (tiredness, respiratory diseases, pain, coordination, concentration, beta blockers, balance, access to health professionals). The current model aggregates all of these factors in the variable "Ability to Engage in Physical Activity"

The effect of Ability to Engage in Physical Activity is represented as a graphical function. The responses provided by subject matter experts indicated the relationship between ability to engage in physical activity and physical activity level was strong, medium, medium, and weak. This spectrum of responses allowed for the use of an s-shaped graph to be used to represent the relationship in the model. The curve was anchored with a normal relationship (ratio value of 1) provided an effect value of 0.2. This value of 0.2, once weighted, enables the variable Percentage of Free Time Available for Physical Activity to provide an initial flow value of 1.1, thus aligning with published literature.

Leisure Time Available

The stock Leisure Time Available represents the amount of time available per day for leisure activities. The stock is impacted by three outflows: Daily Recreational Physical Activity, Daily Utilitarian Physical Activity, and Non-Physical Activity Leisure Time.

Daily Utilitarian Physical Activity

The flow Daily Utilitarian Physical Activity is governed by the effect of the Neighbourhood Environmental Walkability Scale (NEWS). NEWS was selected as it encompassed a number of factors that impacted utilitarian physical activity in the PHSA CLD. Table 4 outlines the relationship between CLD factors and NEWS factors.

Factor in PHSA CLD (6)	Corresponding NEWS Measure
Accessibility to Shops	Proximity to nonresidential uses
	Ease of access to nonresidential uses
Sidewalk Presence and Maintenance	Street connectivity
	Walking/cycling facilities
Aesthetics	Aesthetics
Perceived Environmental Safety	Pedestrian safety from traffic
	Safety from crime

Table 4: CLD Factors and Corresponding NEWS Measures

Of the nine factors measured by NEWS, only residential density (the type of housing existing in the neighbourhood) did not appear to have a corresponding measure within the PHSA CLD. As the NEWS categorizes neighbourhoods into three categories (low walkability, medium walkability, and high walkability), a normalized scale was used in the model to represent this. Using the normalized scale rating of 0-10, the scale was divided into three categories: low walkability (rating of < 4), medium walkability (rating 4.1-6) and high walkability (rating of > 6). The scale was used as it replicates the categorization used by Kerr et al. (57) and Saelens et al. (58).

The graphical function used is an s-shaped pattern with a positive slope. The positive slop is determined based upon the evidence provided through subject matter expert interviews that as the characteristics encompassing the NEWS scale increase, one's partaking in utilitarian physical activity increases in an s-shaped pattern. The

model was calibrated to provide an initial value of 12 minutes of utilitarian physical activity per day. The assumption was made that the individual would be in an environment classified as low walkability, with a NEWS score of 4. A value of 4 is in alignment with the finding that of the 69 largest communities in British Columbia, the average walk score was 4.49 (111). Based upon the current initial value of the stock Leisure Time available, the graphical function curve also provides an increase of 10 minutes of physical activity from the initial 12 minutes one would move into an area of high walkability, as this matches results found by Saelens (58) in a 2003 study where those living in a high walkability area engaged in 70 minutes more of physical activity per week than those in low walkability areas.

Daily Recreational Physical Activity

The flow Daily Recreational Physical Activity is governed by the effect of the number of recreational facilities within a buffer zone. The number of recreational facilities represents the variable Sports Infrastructure from the PHSA CLD. This effect is captured in a graphical function, indicating that as the number of facilities increases in comparison with the normal number of facilities expected, one makes the decision to allocate more leisure time towards recreational physical activity. This graphical function is calibrated to provide an initial value of twelve minutes per day of daily recreational physical activity. The graphical function itself is a positively sloped s-shaped curve. The curve was calibrated to provide an increase of five more minutes of recreational physical activity per day when the ratio increases to greater than four, indicating there are greater than four exercise facilities within one's buffer zone. The value of five minutes was that found in a Swedish study that found participants with more than four exercise facilities within their buffer zones (1000 meters from their household) spent on average 5.4 more minutes in moderate to vigorous physical activity per day, compared to those with no exercise facilities within their buffer zones (59). Further studies also support the relationship between exercise facilities and exercise prevalence, however they lack supportive causal data to aid in the development of the graphical function (60).

Daily Physical Activity

By definition, daily Physical Activity is the combination of both one's recreational and utilitarian physical activity. Statistics Canada estimates that in 2009, the average Canadian engaged in 24 minutes of moderate physical activity per day (61), which represents the mean average amount of physical activity for an individual classified as sedentary according to the PAL guidelines. We assumed that these 24 minutes would be equally allocated to 12 minutes of recreational daily physical activity and 12 minutes of utilitarian physical activity. In attempting to determine whether or not such an allocation proves to be valid, two references support such an allocation. One report indicates that almost six in ten Canadians report walking as a mode of transportation "at least sometimes," thus proving some sort of daily utilitarian physical activity is plausible. Second, with the with the average walking trip being one kilometer (62), and the average walking speed of 12 min/km (62), the average trip would amount to roughly 12 minutes, aligning with the allocation see for daily physical activity.

Physical Activity Coefficient

To operationalize the connection between an individual's volume of daily physical activity and the physical activity coefficient used in the energy expenditure equation, a five-step process was applied.

1. The volume of activity was determined.
2. The volume of activity was translated to an activity category.
3. The activity category was translated to a PAL level
4. The PAL level was translated to a PA factor.
5. The PA factor was translated into a corresponding effect onto the physical activity coefficient used in the energy expenditure equation.

For modeling purposes, all physical activity levels were standardized to indicate a value of moderate physical activity. In order to move reach step 4, the variable

PAL point per minute of moderate PA and PAL was used. A graphical function was used due to the non-linear nature of the relationship between volume of moderate daily physical activity and the corresponding PAL. The graphical function was calculated using the lower value of the volume of physical activity to correspond to the midpoint of the PAL range. For example, a value of 61 minutes provides a PAL value of 1.745 in the graphical function.

Step 5 is represented in the model by the variable Effect of PAL of Physical Activity Coefficient. Validation of the graphical function was completed by comparing the multiplication of the physical activity coefficient provided through the energy expenditure equation with the values from the graphical function values. See section 3.4 Model Calibration for more information on how this graphical function was calculated.

3.2.3 Mental well-being sector

Perceived Weight Bias

The initial value for perceived weight bias was selected to be 0.06, indicating a low perceived weight bias. This value was selected as the prototype individual's BMI falls within the normal BMI range, thus having a greater potential to not be subject to weight bias. In the model, perceived weight bias is influenced only by one's BMI. The variable Effect of BMI on Perceived Weight Bias represents this. The effect is an s-shaped curve and was created based upon data from Puhl, who found that on average a person's chances of being discriminated against because of weight become higher as their body weight increases (64). Puhl found 10 percent of overweight women reported weight discrimination, 20 percent of obese women reported weight discrimination and 45 percent of very obese women reported weight discrimination, while for men, with 3 percent of overweight, 6 percent of obese and 28 percent of very obese men reporting weight discrimination. Further studies have also indicated an increasing presence of weight bias as one's weight increases, with a second study finding that found that overweight respondents were 12 times more likely, obese respondents were 37 times more likely, and severely obese respondents were 100 times more likely than normal-weight respondents

to report employment discrimination (12). Based upon these figures, the graphical function was created using the average of statistics found for men and women in the study conducted by Puhl (12). The output of the graphical function when the BMI falls within the normal range and below is zero. The output increases at an exponential rate as one's BMI increases to align with the exponential increases seen in the literature.

Depression

The variable Actual Depression Level is represents the current level of depression using the Beck's Depression Inventory (BDI), which is a 21-item test that measures the presence and degree of depression in adolescents and adults consistent with the DSM-IV. The scale is measured from 0-63, with measures of 0–9 indicates that a person is not depressed, 10–18 indicates mild-moderate depression, 19–29 indicates moderate-severe depression and 30–63 indicates severe depression (64). The variable Maximum Depression Level represents a value of 63, or the maximum score on the BDI. One's actual depression level is calculated using Equation 5.

Equation 5:

$$Actual\ depression\ level\ -\ (1/2 * Maximum\_Level\_of\_Depression \\ * Effect\_of\_Stress\_Ratio\_of\_Depression) + (1/2 * Maximum\_Level\_of\_Depression \\ * Ef\ ect\_of\_Perceived\_Weight\_Bias\_on\_Depression)$$

The effect of both the Stress Ratio and Perceived Weight Bias are weighed equally due to the lack of available data on the weighting factors. The Effect of Perceived Weight Bias on Depression is represented as a graphical function. Literature reviews highlight the lack of longitudinal research on the relationship between weight bias internalization and depression. Due to this research gap, a graphical function was calibrated based upon an assumption that if one were experiencing a maximum value for Perceived Weight Bias (a value of 1 in the model), this would indicate a score of 18 on the BDI, indicating mild to moderate depression. The graphical function is an s-shaped pattern, as it aligns with the responses provided by six experts interviewed by Giabbanelli

(53). These experts indicated the relationship between depression to be very strong, strong (three indicated), medium, and weak. From this, the use of an s-shaped curve is appropriate as it has the potential to provide the relational responses indicated by experts.

The Effect of Stress Ratio of Depression also impacts one's actual depression level. Studies have demonstrated the relationship between stress and depression through a number of mechanisms (65) (66), however studies have failed to investigate the quantitative nature of the relationship. Because of this, the graphical function used to represent the effect provides a response that if one's stress ratio increases to the maximum value of 5; this results in a BDI score of 18, indicating mild-moderate depression.

Antidepressant Use

The prescription of antidepressants is based upon one's level of depression. Clinical guidelines indicate that antidepressants are recommended for those who present with symptoms of at least moderate depression (67). Based upon these recommendations, the variable Effect of Depression on Antidepressant Use provides a value of one, indicating no antidepressant use. The stock Normal Antidepressant Use is initialized to a value of 1, providing an initial Antidepressant Use Ratio of 1. This structure representing an actual value, a normal value, and a ratio of the two is included as it lends itself to providing a more realistic picture of the effects of antidepressant use on weight gain. With this structure, as one becomes more depressant and triggers the prescription of antidepressants, the effect of antidepressants on energy intake eventually decreases over time, until one achieves a new normal intake level. For example, as one is initially prescribed an antidepressant, we would see weight gain over a particular period of time. However as one's Normal Antidepressant Use increases to match one's Antidepressant Use, we see the effect on energy intake (potential weight gain) diminish over time. This allows for the model to provide a realistic weight change in alignment with published literature. Without this structure, one's antidepressant use would continue influence one's energy intake, leading to potentially a continuous weight gain over the course of time one is on the antidepressant.

Effect of Antidepressants Use Ratio on Energy Intake

The Target Effect of Antidepressants Use Ratio on Energy Intake is a graphical function that was calibrated based upon published literature stating the changes in weight seen in different antidepressants over time. The impact of antidepressants on weight has been shown be shown to vary upon the type of antidepressant (68). With some antidepressants, an initial weight loss can be seen over the course of the first few weeks (4-12 weeks), however over the long term, weight gain is common. Based upon a meta-analysis of 11 different antidepressants, the average weight gain seen over a medium and long-term treatment (greater than four months) was 0.89kg (68). However the study was unclear of the duration of such weight gain (whether it was per month, or for the duration of the prescription). Further reviews conducted by Schwartz et al. (69) found among five different antidepressants, the average weight gain seen was 2.93kg while the duration of such weight gain was also varied among the specific type of antidepressant. Based upon the variation seen in published literature, the Target Effect of Antidepressants Use Ratio on Energy Intake is set to achieve a weight gain of 2.93 kg over a six-month period when the Antidepressant Ratio is at its maximum value of 2.

The Actual Effect of Antidepressants Use Ratio on Energy Intake is a first order smooth function of the target effect. A smooth function was used as it takes into account the delay time that represents the antidepressants physiological impact on the body and its mechanism in which it works to promote weight gain. Without the smooth function, the effect of the antidepressants would be seen immediately in the model, thus not being in alignment with real life patterns of weight gain seen in published studies, which indicate weight gain due to antidepressants to be gradual over time.

Actual Stress

Actual Stress is influenced by one's physical activity level (PAL). Studies have found that physical activity can be used to reduce stress through a number of mechanisms (70) (71). Research has shown that physical activity is an effective means of reducing

anxiety and various indices of stress among adults (72). However, there is a lack of published literature quantifying such a relationship. The graphical function Effect of PAL on Stress was calibrated to provide a reduction in one's stress level as one's stress level. The initial value of the curve was calibrated to provide a Stress Ratio of 1 based upon the individual's initial PAL of 1.15, thus providing an initial equilibrium with regards to one's initial stress level.

Actual Emotional Eating Level

The actual emotional eating level is influenced by the variable Effect of Stress on Emotional Eating. This effect is represented as a graphical function. Interviews conducted with experts indicated the relationship between stress and emotional eating to be medium (two indicated), weak, and non-existent. Due to this spectrum of answers, an s-shaped curve was used in the graphical function to allow for a different level of effect to be seen. The curve was calibrated to provide an initial Emotional Eating Ratio of 1 to ensure an equilibrium level upon initialization of the simulation. The curve itself allows for a maximum increase of one's emotional eating level of three times the normal value. As the literature has focused on the end result of emotional eating (i.e. increased consumption) rather than the concept of an emotional eating level, an assumption was made to indicate the exact nature of the relationship, as well as the maximum increase that one's stress ratio could have on one's emotional eating level.

Effect of Emotional Eating on Energy Intake

The Effect of Emotional Eating on Energy Intake is a graphical function that was calibrated based upon previous studies stating the changes in weight and appetite due to a variety of emotional changes. Experimental studies have shown that emotional eaters consume more energy-dense foods in response to negative emotions than non-emotional eaters (73). Furthermore, a study by Macht (74) found that higher emotional eating was related to eating more sweet and non-sweet energy-dense foods, while it was unrelated to

the consumption of vegetables and fruit/berries, supporting the hypothesis that emotional eating is specifically related to the increased eating of sweet and high-fat foods.

Published literature has shown both increases and also decreases in one's appetite in response to emotional stress. In this model, the assumption is made that the prototype individual's energy intake increases in response to increased levels of emotional stress. As studies have focused on the overall behavior (i.e. eating more, eating less) (74) rather than quantifying the nature of such behavior (i.e. How much more?), an assumption was made to allow for a maximum of a 10% increase above one's energy expenditure when the maximum ratio of emotional eating was reached. The use of an s-shaped curve for the graphical function allows for the inclusion of experts' opinions on the relationship between emotional eating on healthy eating, as four experts interviewed indicated this relationship to be strong, medium, and very weak. (53) One expert was unsure of the relationship. Due to the spectrum of responses, the s-shaped curve allows for each effect's strength to potentially be applied, depending on the ratio emotional eating ratio.

3.2.4 Food Environment Sector

Actual Annual Income

The variable Actual Annual Income is calculated by multiplying one's Potential Annual Income by the variable Effect of Perceived Weight Bias on SES. One's Potential Annual Income was taken based upon the median total income for families in British Columbia (75). The initial value of $58 500 represents the median income in 2005. The parameter Annual Salary Inflation is 0.032, indicating on average, the annual salary inflation is 3.2% (75).

The Effect of Perceived Weight Bias on SES is a graphical function representing the effect of one's perceived weight bias on SES. It should be noted that annual income was selected as a proxy representation of the concept SES (socioeconomic status) that was included in the PHSA CLD. Although the concept of socioeconomic status commonly encompasses a combination of education, income and occupation (76) researchers have stated that SES status is a latent variable cannot be directly measured

(77) and there are no mechanical devises that permit direct and relatively precise measurements of SES.

The graphical function was calibrated based upon literature stating that a wage penalty is present as one's weight increases. A number of studies have measured such an effect. Table 5 outlines the quantification of the graphical function used.

BMI	Perceived Weight Bias	Reduction in Wage
Normal	0	0
Overweight	0.065	1%
Obese: Class 1	0.130	4.5%
Obese: Class 2	0.450	10%
Obese: Class 3	0.80	15.4%

Table 5: Weight Bias and Wage Reduction

All values in the Reduction in Wage are calculated. For the Obese: Class 1 figure, the calculation was made based upon findings that indicated obese men experienced on average 1-3.4% reduction in wage, women 2.3 - 6.1%, mild obese women 5.8%, and mild obese white black woman 3.3% (12) For Obese: Class 3, the value of 15.4% was taken based upon finding indicating severely obese white women faced a 24% wage penalty, severely obese white men 19.6%, severely obese black women 14.6%, and severely black men 3.5% (12) The values for Obese Class 2 was calculated based upon the average of Class 1 and 3, while the value of Overweight was based upon an statistics indicating As a consequence, overweight and obese employees earn 1% to 6% less than normal-weight people in comparable positions, and this salary difference is greater for obese women than obese men (12) (46).

Percentage of Annual Income Allocated for food

The percentage of Annual Income Allocated for Food is calculated by dividing the Average Annual Cost of Purchasing Healthy Food by the Actual Annual Income. The Average Annual Cost of Purchasing Healthy Food represents the annual cost of purchasing the Nutritious Food Basket. The Nutritious Food Basket is a survey tool that

is a measure of the cost of basic healthy eating that represents current nutrition recommendations and average food purchasing patterns. Food costing is used to monitor both affordability and accessibility of foods by relating the cost of the food basket to individual/ family incomes (80). The initial value of the Nutritious Food Basket ($7853.52) represents the annual cost of purchasing the food basket for a family of four in British Columbia in 2005. The parameter Annual Food Cost Inflation represents the annual increase in the cost of the food basket. The value was set at 4% based upon historical costs of the basket (80) (81) (82) (83).

The initial value of one's annual income allocated for food was calculated to be 13.4%. The initial value of the stock Normal Percentage of Annual Income Spent on Food is 12.9%, based upon 2010 statistics indicating 12.9% of household income was spent on food expenditures (84).

Target Effect of Income Ratio on Ease of Purchasing Healthy Foods

The variable Target Effect of Income Ratio on Ease of Purchasing Healthy Foods represents one's ability to purchase healthy food based upon the percentage of one's annual income that is need to be allocated towards purchasing the nutritious food basket. Given the grocery bill is a flexible cost, families often sacrifice quantity and quality of food to meet fixed costs, like the rent, utilities, and other essential costs of daily living (82) mind, the assumption is made that the Percentage of Annual Income Allocated for Food Ratio increases, it makes it more difficult to purchase healthy nutritious foods. This assumption is based upon the fact that on research findings indicating eating a healthy diet versus an unhealthy one is more expensive (85).

Discussions with subject matter experts indicated that as one's income available for food decreases, one does not in turn decrease their caloric intake – said otherwise, they do not continue to purchase the same foods, just less of such foods. Instead, individuals in the Western world continue to aim to purchase the same calorie levels, and do so through the purchasing of lower nutrient, more energy dense foods. Purchasing of such foods often leads to increased caloric intake than normal. This finding is supported by research finding that low income Canadians eat fewer servings of vegetables, fruit and

milk than wealthier Canadians (81) Furthermore, people with lower socio-economic status (SES) have poorer dietary quality on average than more socioeconomically advantaged people (86), one can speculate this is due in part to the purchasing of less nutrition foods, which in turn, are often replaced by higher energy dense foods.

3.3 Model Calibration

Physical Activity Sector

The physical activity coefficient used in the energy expenditure equation developed by Hall was set at of 7 +/- 4 kcal/kg/day. As this energy expenditure equation was calibrated to match the reference mode behavior of the NHANES data (48), there is no published indication of what volume of physical activity a value of 7 represents, nor what scale was used in determining the value. Due to these limitations in the information available, a variable Effect of PAL on Physical Activity Coefficient was introduced. This variable was calibrated using the Institute of Medicine equations for estimating energy requirements (EER) (112). Equation 7 outlines the equation for men, while Equation 8 outlines the equation used for women

Equation 7

$$EER = 662 - (9.53 \; x \; age \; [y]) + PA \; x \; \{ (15.91 \; x \; weight \; [kg]) + (539.6 \; x \; height \; [m]) \}$$

Equation 8

$$EER = 354 - (6.91 \; x \; age \; [y]) + PA \; x \; \{ (9.36 \; x \; weight \; [kg]) + (726 \; x \; height \; [m]) \}$$

Based upon the five-step process outlined in 3.3.2 Physical Activity Sector (subsector Physical Activity Coefficient), Table 6 provides an overview of steps 1 through 4.

Volume of Moderate Physical Activity (min/day)	Activity Category (112)	PAL (112)	PAL Value Used in Model
< 30	Sedentary	1.0-1.39	1.195
30-60	Low Active	1.4-1.59	1.495
61-180	Active	1.6-1.89	1.745
>180	Very Active	1.9-2.5	2.2

Table 6: Physical Activity sector conversion factors

Using the four different physical activity categories available for this equation, the EER was calculated for both men and women for each of the four levels of categories of physical activity. Table 7 outlines the calculations made.

Physical Activity Category	EER: Men	EER: Women	Average
Sedentary	2358	1997	2178
Low Active	2582	2223	2402
Active	2866	2506	2686
Very Active	3333	2845	3089

Table 7: EER Calculations

The graphical function Effect of PAL on Physical Activity Coefficient was calibrated using the average EER calculated from the Institute of Medicine equation. This variable was included in the model as a way to ensure that the energy expenditure equation produces a realistic output when one's physical activity changes.   This graphical function provides an output effect that is multiplied with the initial value of 7 to reproduce an energy expenditure that matches that of the average values found. Table 8 provides information on the multiplication factors used as well as the outcome of the energy expenditure equation used in the model using these factors.

Volume of Physical	PAL (midpoint	Multiplication Factor in Effect	Physical Activity Coefficient	Energy Expenditure	Estimated Energy

Activity	of range)	of PAL on Physical Activity Coefficient		(Model equation)	Requirement (Men and Women average)
30 min	1.195	1.33	1.33*7 = 9.31	2310	2178
60 min	1.495	1.845	1.33*7 = 12.915	2563	2402
90 min	1.596	2.03	2.03*7 = 14.21	2655	2686
180 min	2.2	2.884	2.884*7 = 20.188	3075	3089

Table 8: Physical Activity Calculations

4 Model Simulation Results

4.1 Simulation Characteristics

The model is calibrated to represent an average British Columbia. Table 9 provides the characteristics of the prototype individual.

Characteristic	Value	Description	Source
Age	41 years	Average age of British Columbian in 2012	(87)
Sex	Male	-	-
Weight	70.72kg	Calculation based upon weight needed to obtain average BMI of Canadians based upon average height.	(108) (109)
Height	1.69	Average height combined of Canadian men and women in 2005	(109)
BMI	24.76	Average combined BMI of Canadian men and women in 2005	(109)
Daily PA	24 minutes	Volume of physical activity is in alignment with standards for sedentary individual	-

Table 9: Simulation prototype characteristics

The time horizon for the model is set to four years. The rationale for the time horizon selection is to an average length of time a political party is in power within the provincial government in British Columbia (88). The time increment for the model is set

to 1 day as this allows for the representation of one's daily energy intake and daily energy expenditure to be included in the model. The decision to use initialize the model using data from 2005 (when available) was due to an analysis of the BMI pattern seen over time. The behaviour pattern seen appeared to begin its increase in 2005.

The following section highlights the simulation results of the model based upon the above prototype individual. Following discussion of the results, sensitivity tests will be presented and discussed based upon changes in parameter values for the prototype individual. As the model allows for a range of prototypes to be tested, a second individual will be presented along with the results from the simulation runs.

4.2 Simulation Results

The aim of the model was to explore how the interaction between factors within one's physiology, physical activity, mental well-being, and the food environment play a role in one's weight over time. Figure 10 shows the simulation results of the prototype individual's body weight over the course of the four-year simulation period.
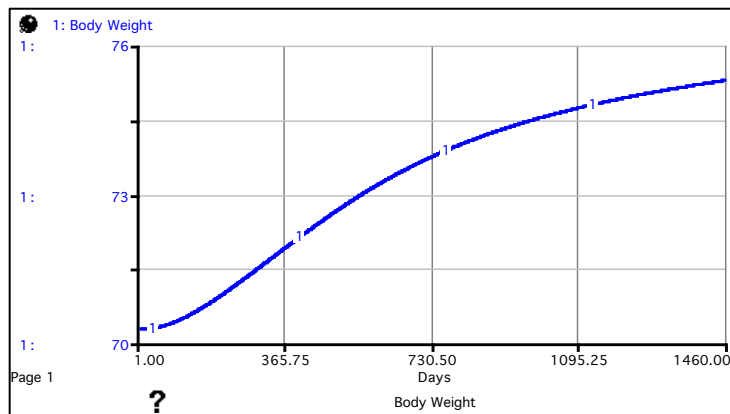

Figure 10: Simulation Results: Body Weight

The behavior demonstrates an s-shaped growth pattern. The increase in weight is due to an imbalance between one's energy intake and energy expenditure. Investigating the energy expenditure side, Figure 11 provides the results of one's change in physical activity. The decrease in physical activity is due the increase in weight driving one's

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Perceived Weight Bias, which acts as a barrier to physical activity, reducing the percentage of one's free time that they time one allocates to physical activity.
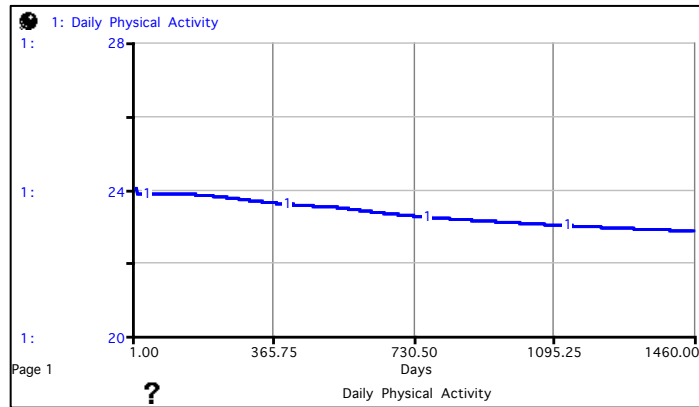
Figure 11: Simulation Results: Daily Physical Activity

The decrease seen in physical activity (and thus energy expenditure) and the increase seen in energy intake creates a positive energy balance. This initial balance leads to a number of effects. First, this triggers a balancing loop that works to return to a zero energy balance. This loop causes an increase in both fat mass and fat free mass that increases the energy expenditure to a level that matches the energy intake, eliminating the energy balance. As there is a only a small decrease in one's physical activity, we can rule out physical activity as a driver causing a decrease in energy expenditure that may have led to the weight gain seen.

In the assessment of determining what changes in energy intake could have led to the change in weight seen over time, we see one's energy intake being driven initially by the food environment sector. As the initial percentage of income (13.4%) allocated towards food is higher than the normal value (12.9%), we see this discrepancy increase the Percentage of Annual Income Allocated for Food Ratio. In reality, an increase in this ratio represents an increase in the difficulty of purchasing healthy foods within a constant budget, thus leading an individual to purchase cheaper, more energy dense foods in order to match the same volume of food purchased. This leads to an increase in the Target Effect of Income on ratio on Ease of Purchasing Healthy Foods, which in turn, leads to an increase in energy intake.

The initial weight gain leads to an increase in the Perceived Weight Bias, as seen in Figure 12.
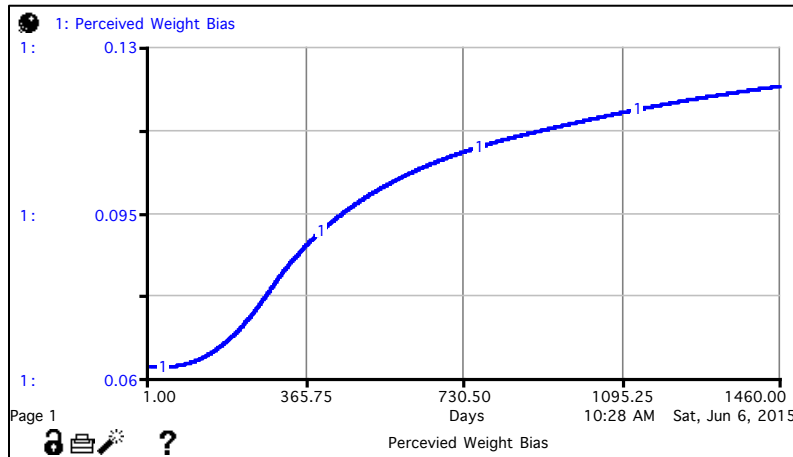
Figure 12: Simulation Results: Perceived Weight Bias

The graph shows that the change in Perceived Weight Bias is minimal. This is due to an initial value of ~ 0, as it was assumed since the individual's initial BMI falls within the normal category, they would not be subject to any weight bias. Furthermore, although the weight gain presented over time does increase the individual's BMI from the normal category to the overweight category, the individual would only be subject to minimal weight bias at this BMI level. This finding is in alignment with literature indicating the weight bias seen in overweight subjects to be low (only three percent of overweight men indicated they were subject to weight bias). Due to the low value of Perceived Weight Bias, it does not trigger initially the reinforcing loops that impact the mental well-being sector, thus we see no effect from one's emotional eating or antidepressant use on increasing energy intake, as shown in Figures 13 and 14 respectively.
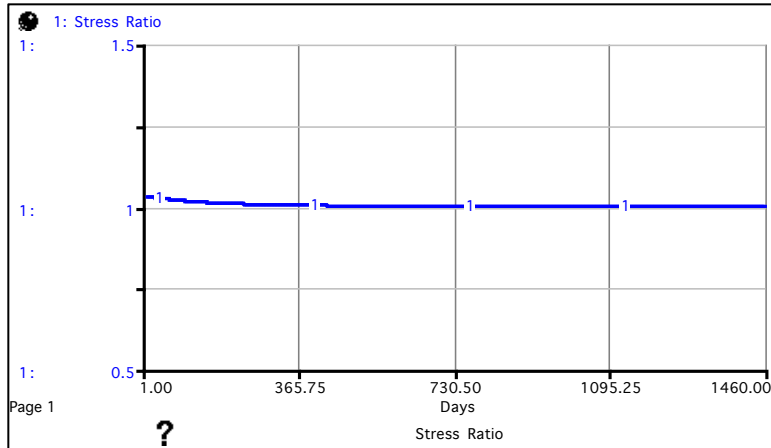
Figure 13: Simulation Result: Stress Ratio
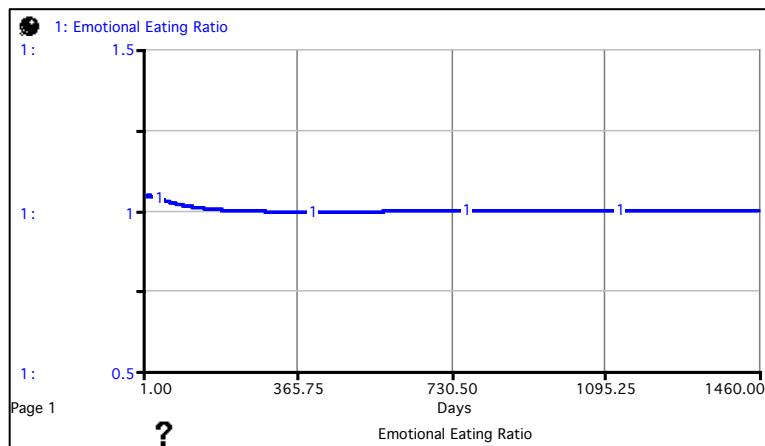
Figure 14: Simulation result: Emotional Eating Ratio

The initial value of greater than 1 in both the Stress Ratio (1.04) and Emotional Eating Ratio (1.06) are as a result of the inability to initializing the graphical functions influencing both the Actual Stress Value and Actual Emotional Eating Level to a specific value of 1 using the iThink software. The slight increases above 1 are not significant enough to alter the behavioral pattern seen in body weight and therefore their effect can be neglected.

Looking at the pattern of body weight, initially we see a period of little to no movement in one's weight. This can be attributed to the delays seen in the variables driving the change in energy intake, specifically the Effect of the Percentage of Annual Income Allocated for Food. The growth in weight gain is reduced due to a number of

factors. As the Normal Percentage of Income Allocated for Food changes to match that of the Percentage of Income Allocated for Food, we see the ratio of the two works to reach a value of 1. As the ratio moves towards a value of 1, this reduces the impact the variable Target Effect of Income Ratio on Ease of Purchasing Healthy Foods. The growth seen in weight loss is also balanced by the effects of the physiology of the individual. The increase in weight is counterbalanced by an increase in fat and fat free mass, thus increasing the energy expenditure of the body. Overall we see that the body works to achieve a new set point for energy intake and energy expenditure, as seen in Figure 15.
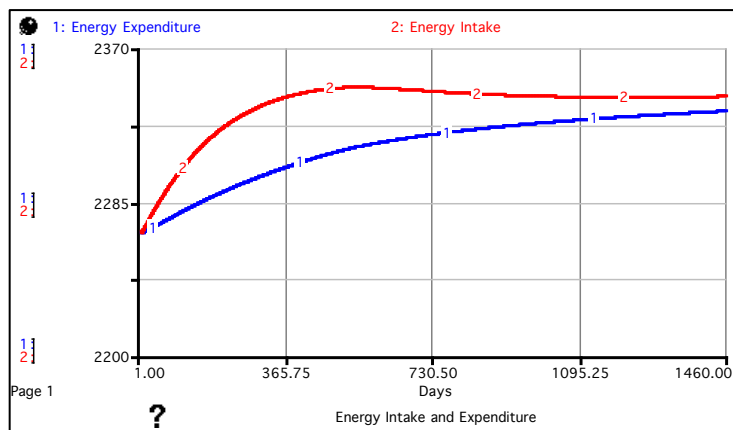
Figure 15: Simulation Result: Energy Intake (red) and Energy Expenditure (blue)

The continued increase seen in body weight can be attributed to the reinforcing loop that continues to increase one's Perceived Weight Bias. This continually increase in Perceived Weight Bias further prevents one from achieving their potential income, thus increasing the percentage of one's income they allocate towards foods and continuing to create a discrepancy between the Percentage of Income Allocated for Food and the Normal Percentage of Income Allocated for Food.

5 Model Validation

Although the lack of formal, objective measures available for validation testing may be limited for the model, one can also validate the structure of the model based upon semi-formal or subjective means (89). One subjective validation test focuses on

validating the model with some respect to the overall purpose of the model, or judging the model's usefulness as with some respect to its purpose. As the purpose of the model was to explore how the interactions between physiology, physical activity, mental wellbeing, and the food environment can impact one's weight over time, the model successfully serves as a dynamic hypothesis to achieve this purpose. As Sterman states that no model can ever truly verified or validated because all models are wrong (15), this statement lends itself to focusing more on validating or verifying the purpose of the model and the process used in building the model in efforts to gain confidence in how well the model structure represents its counterpart in the real-world.   Sterman has also outlined twelve different groups of assessment tests that can be used to evaluate the validity and sensitivity of a model (15). Seven of these twelve groups will be discussed in the following section.

5.1 Behavior Reproduction

The behavior reproduction test seeks to see if the model reproduces the behavior of interest in the system either qualitatively or quantitatively (15). It further looks to see if the model endogenously generates the symptoms of difficulty motivating the study. One can answer these questions by either performing statistically analysis or by completing a qualitative assessment output of the model, looking at different modes of behavior and shape of variables.   Due to the lack of objective measures available, the change is body weight serves as the primary variable to validate the overall model behavior. The validation measure used is the percentage weight change found in the National Longitudinal Survey of Youth. The survey sampled 12,686 young men and women who reported their weight biennially from 1986 to 2004. The largest change between two successive reports was 3.6%, indicating the greatest weight gain seen was 1.8% per year (27). Table 10 outlines the percent growth in body weight seen in the model.

Time Frame	End Weight (kg)	Percent Change
Day 1	70.72	
Day 1-365	71.95	1.7%
Day 366 – 730	73.79	2.55%
Day 731 – 1095	74.77	1.3%
Day 1096 -1460	75.32	0.7%

Table 10: Simulation Results: Body Weight

Overall we see that the percent weight change is in alignment with the findings from the National Longitudinal Survey of Youth study for all but year two (day 366-730). Using the findings from the National Longitudinal Survey of Youth does have limitations. First, the study looked at weight changes in youth, which differ from the prototype adult seen in the model. Second, as the literature has shown that antidepressant use can cause up weight gain of up to 3.1kg in one year. Based upon the prototype individual, this statistic alone could account for a 4.4% increase in body weight over year one, well above the rate found by the National Longitudinal Survey of Youth study. Although the antidepressant loop is not active in this simulation, it should be taken into account when analyzing the annual weight gain of the simulation prototype individual.

The results seen in body weight provide insight on the validation of the scale for the three graphical functions used that impact energy intake. For the graphical function Effect of Antidepressant Use on Energy Intake, the scale of the effect was set from 1 – 1.04. This scale was set to provide a maximum of 4% increase in energy intake as this would result in a maximum of 2.82 kg gained in one year, which is in alignment with the average weight gain seen in those using antidepressants (69). For the other two graphical functions (Effect of Ease of Purchasing Healthy Foods on Energy Intake and Effect of Emotional Eating on Energy Intake), an arbitrary scale was set from 1-1.1. Based upon the results seen for the change in body weight, one can assess that a maximum value of 1.1 serves as a plausible upper limit for each variable, however further research is needed to be conducted in order to further gain confidence in these values.

5.2 Boundary Adequacy

Boundary adequacy tests assess the appropriateness of the model boundary for the purpose at hand. These tests assess whether or not important concepts for addressing the problem endogenous to the model are absent from the model structure (15). As the initial model boundary was set based upon the factors included in the CLD created by PHSA the question to be answered is whether or not the factors selected from the CLD that are included in the model are represent an adequate boundary to produce a plausible behavior over the time horizon. As the model structure does produce a plausible behavior pattern of body weight over time, this indicates the current model boundary does include feedback loops among the four sectors necessary to produce the behavior. However, a number of factors could still be added to the model in order to improve the boundary adequacy. For example, several factors had to be simplified from the PHSA's CLD given current gaps in the evidence. The addition of factors is discussed in Future Work.

5.3 Dimensional Consistency

Dimensional consistency seeks to ensure that each equation is dimensionally consistent without the use of parameters having no real world meaning (15). The Unit Check function of the iThink software can be used as an aid to check for unit consistency. The model does meet the criteria for dimension consistency according to iThink.

5.4 Extreme Conditions

The purpose of extreme conditions tests is to determine if each equation make sense even when its inputs take on extreme values and to ensure the model responds plausibly when subjected to extreme shocks and values to parameters (15).   These tests look at assessing the model's robustness, as the model should behave in a realistic manner no matter how extreme the inputs or policies imposed on the model are (15).

Physical Activity Extreme Condition Test

The extreme condition test performed for the physical activity sector was to assess the behavior of the model when there are no barriers to physical activity and when one's ability to engage in physical activity is set to its maximum value. Equation 6 outlines the equation used for this test.

Equation 6

Percentage of Free Time Allocated for Physical Activity
$$= (0.5 * Effect\_of\_Ability\_to\_Engage\_in\_PA\_on\_PA + 0.5 \\ * Effect\_of\_Barriers\_Engaging\_in\_PA\_on\_PA) * 0 + 1$$

Both effects were negated, and a value of 1 was set for the variable. The results for Daily Physical Activity are shown in Figure 16.
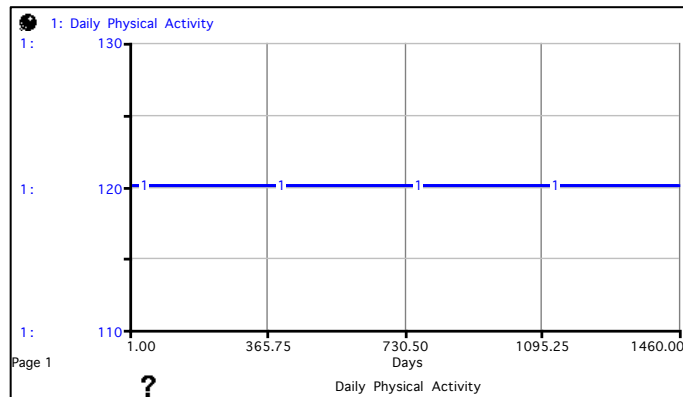
Figure 16: Simulation Result: Daily Physical Activity

The results seen in Daily Physical Activity are expected, as the extreme test allows for all of the 5.5 hours of Free Time Available to be allocated towards Leisure Time Available.

Looking at the resulting behavior in one's body weight Figure 17, we actually see the same pattern of weight gain as in the initial simulation, however at a stronger rate (greater weight gain seen).

Figure 17: Extreme Condition Simulation Result: Body Weight. The blue graph indicates initial simulation run. Red line indicates simulation result from physical activity extreme test.

At the end of the simulation we see a weight of 76.48 kg, higher than the 75.32kg seen from the initial simulation run. When analyzing this taking into account only the current model structure, the results are as expected. As one's physical activity increases, so does his/her energy expenditure (via the physical activity coefficient). As formula for the energy intake is formulated around one's energy expenditure, any increase in energy expenditure will ultimately lead to an increase in intake too. In part, this action is equivalent to what happens in the real world, as if one has a goal to maintain one's weight with an increase in physical activity, one would expect to see an increase in energy intake. The increase in body weight seen is driven by the exact same mechanisms as in the initial simulation run. Although the rationale for such weight gain is valid, the current model formulation lacks a decision rule that would take into account the balance between one's physical activity level and energy intake. One would expect that an individual performing 120 minutes of moderate physical activity per day would not be expecting to gain weight (albeit possibly muscle mass, however the model does not explicitly take into account any muscle gained through physical activity). One opportunity to improve the model's response to this extreme condition test would be to add structure in the model that represents an individual's behavioral decision regarding whether or not they are looking to maintain, lose, or gain weight.

Mental Well-Being Extreme Conditions Test

The extreme conditions test selected for the mental well-being sector was to set the Actual Depression Level to the Maximum Depression Level. Figure 18 provides the results for the extreme condition test.
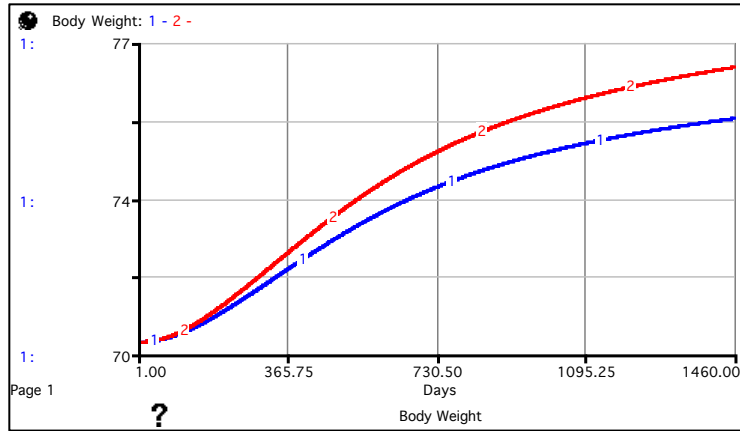

Figure 18: Extreme Condition Simulation Result: Body Weight. The blue graph indicates initial simulation run. Red line indicates simulation result from mental well-being extreme condition test.

Overall we see a greater weight gain in the extreme conditions test. This is due to the fact that this individual is subject to a greater influence of antidepressants (a value of 2 instead of the a normal value of 1 for the variable Antidepressant Use). This in turn causes a greater value for the Antidepressant Use Ratio and subsequently, a greater effect in the Target Effect of Antidepressant Use Ratio on Energy Intake. Here, the concept of Antidepressant Use represents the quantity of antidepressants one individual may be prescribed. As the individual is at the maximum level of depression (a value of 63), the assumption is made that this individual may be on multiple antidepressants, thus increasing his/her potential to be subject to the multiple weight gaining effects seen from the antidepressant mix.

Food Environment Extreme Conditions Test

The extreme conditions test selected for the food environment sector was to set the Potential Annual Income to an initial value of $150 000 instead of the original simulation value of $58 500. Figure 19 provides the results for the extreme condition test.
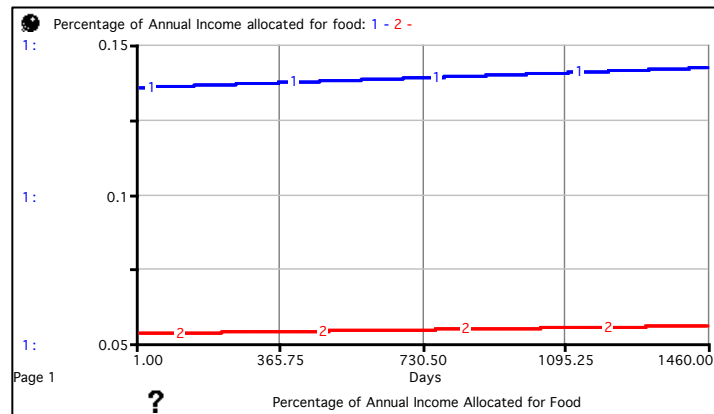
Figure 19: Extreme Condition Simulation Result: Percentage of Annual Income Allocated for Food.
The blue graph indicates initial simulation run. Red line indicates simulation result from food environment extreme condition test.

We see that with a higher income, the Percentage of Annual Income Allocated For Food is decreased significantly. This results in the variable Percentage of Annual Income Allocated For Food Ratio to be less than 1, resulting in no impact of the variable Target Effect of Income Ratio on Ease of Purchasing Healthy Foods on one's energy intake, as evidence by Figure 20, which indicates no weight change over the simulation time.
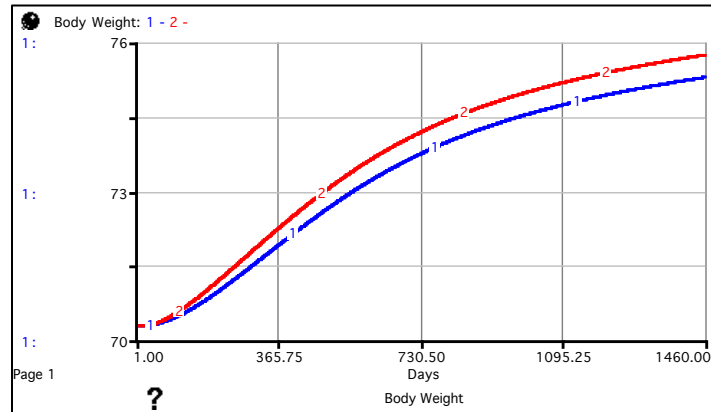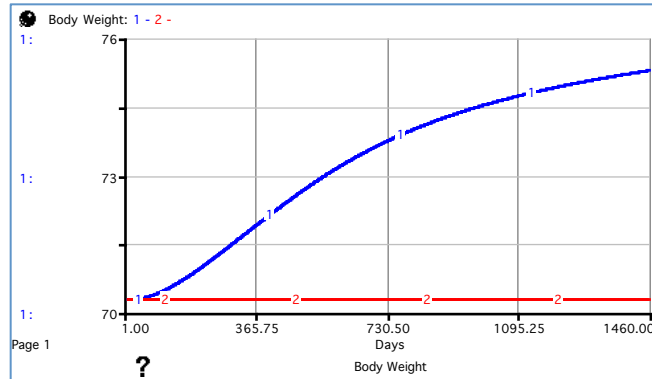
Figure 20: Extreme Condition Simulation Result: Body Weight. The blue graph indicates initial simulation run. Red line indicates simulation result from food environment extreme condition test.

As the prototype individual has a weight within the normal BMI range, the effects of the mental well-being sector on weight are not seen. As the change in weight is solely influencing by the food environment sector in the original simulation, we would expect to no change in weight when the effects on energy intake from this sector are nullified. The results seen in one's body weight would be expected when viewed in terms of the food environment, which no longer acts as a barrier to healthy eating for the individual. In reality, this may not be the true case, as other aspects of the food environment would need to be taken into account to truly see if an extremely high-income level nullifies the barrier effect seen by the food environment

5.5 Model Specifications Tests

Model specification tests include changing the technical specifications of the simulation to determine if the changes alter the behavior of the model. Two different tests were completed – (1) extending the time horizon to eight years (2920 days), and (2) changing the integration time (integration error tests).

Extending Time Horizon

Figure 21 provides the results of the model behavior for body weight based when the time horizon is extended.
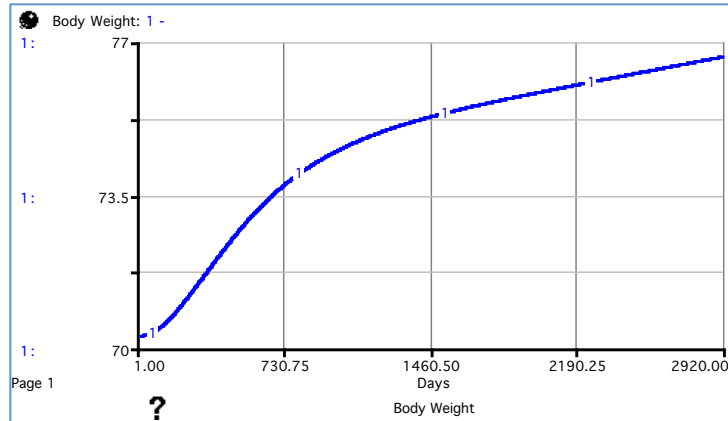
Figure 21 Extending Time Horizon simulation result: Body weight

The behavior seen in one's body weight beyond the initial time horizon period (post-1460 days) can be attributed to the impact of the food environment sector and the physiology sector. We can attribute the continued rise in body weight to the continued discrepancy seen between the Percentage of Annual Income Allocated for Food and the Normal Percentage of Annual Income Allocated for Food. As the historical data shows the rate of growth in price for the food basket rises faster than that of the potential annual income, we see the Percentage of Annual Income Allocated for Food continue to grow. The growth in body weight is counterbalanced somewhat by the physiology sector, where one's energy expenditure due to increases in resting metabolic rates for fat mass and fat free mass also grow, thus attempting to reach a zero energy balance. In reality, we would expect to see potential weight increases if the food environment continues to strengthen its effect as a barrier to healthy eating, however it is unknown to what extend (both in terms of quantity and time span) that such an effect would continue to promote weight gain. One would expect to see this effect level off after some time, as the individual would become stable at a particular weight. In order to achieve such an effect, additional structure would need to be added to the model to account for one's individual decision-making and desire to maintain a particular weight.

Integration Error Tests

Integration error tests seek to determine if the model simulation results are sensitive to the time step or numerical integration method (15). For the purpose of this analysis, the focus will be only on the time step. Table 11 outlines the changes in body weight seen based upon the different time steps

Time Frame	dt: 1 day	dt: 2 days	dt: 0.5 days	dt: 0.01 days
Day 1	70.72kg	70.72kg	70.72kg	70.72kg
Day 366	71.95	72.01kg	71.96kg	71.96kg
Day 731	73.79	73.82kg	73.79kg	73.79kg
Day 1096	74.77	74.82kg	74.77kg	74.77kg
Day 1460	75.32	75.39kg	75.32kg	75.32kg

Table 11: Integration error tests simulation results

A visual analysis of the different dt simulation results indicate there are no major differences between the results based upon the different dt values used. The conclusion can be made that the initial dt time of 1 day yields a correct approximation of the underlying continuous dynamics that are accurate to meet the purpose of the model.

6 Sensitivity Analysis

The transition of the PHSA CLD posed a number of challenges in terms of operationalizing the soft variables that encompass the real world systems of weight and well-being. A number of graphical functions were used to represent the effects conveyed by the different soft variables. As there were a number of challenges and limitations in the creation of such graphical functions, validation of the functions themselves proves difficult. The following section provides simulation results based upon the alterations of a number of graphical functions and parameter values. The purpose of conducting such tests is to identify parts of the model in which a change in a parameter value or graphical function results in a meaningful change in output behaviour. Such parts deemed sensitive pieces of the model can be identified, as a piece where more literature may need to be

conducted to ensure the values included in the model best represent their real world counter parts. The sensitive parameters can also be used by policy makers to identify leverage points in the system that are most responsive to any future policy changes.

The following sections are broken down as followed. For each sector, the results will be presented for one or more parameter changes, along with the results seen in body weight.

6.1 Physical Activity Sector

The parameter changes for the physical activity sector focus on the built environment variables – Number of Facilities in Buffer Zone and the NEWS. The changes made for the simulation runs are summarized in Table 12.

Variable	Initial Value	Value: Run 1	Value: Run 2
Number of Facilities Within Buffer Zone	2	4	1
NEWS	4	8	2

Table 12: Sensitivity Analysis Changes: Physical Activity Sector

The results for the simulation runs can be seen in Figure 22 and Figure 23.
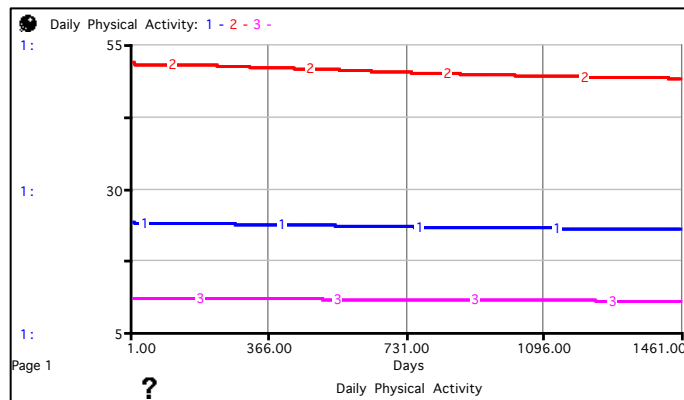
Figure 22: Sensitivity Analysis Physical Activity Sector: Daily Physical Activity
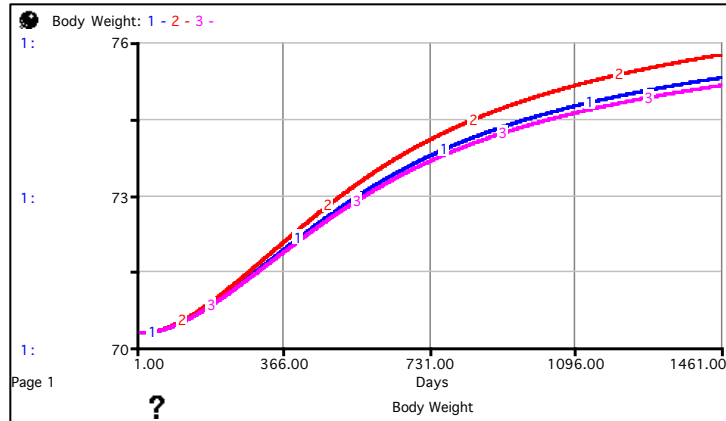
Figure 23: Sensitivity Analysis Physical Activity Sector: Body Weight

With improvements made to the built environment that make the environment more conducive for physical activity, we expect to see an increase in one's daily physical activity. This finding is in alignment with findings of Sallis et al. (90) whose meta-analysis found that availability and proximity to recreation facilities has been associated consistently with greater physical activity among adults. Doubling both parameters resulted in a 115% increase in physical activity at the end of the simulation run (22.85 minutes to 49.25 minutes), while cutting the values in half decreased the physical activity by 55% (to 10.31 minutes). This variation in the results reflect the nature of the s-shaped curves used for the graphical effects that represent the Effect of the Facilities on Time Used for Rec PA and the Effect of NEWS on Time Used for Util PA. As the input values into both of these effects are reduced, the s-shaped pattern of the effect provides a lower output; hence we see a lower value being multiplied against the Leisure Time Available to provide the output value for the Daily Recreational Physical Activity or Daily Utilitarian Physical Activity flows.

The changes in body weight mimic those seen in the initial simulation run. Due to the current formulation of the energy intake flow, we expect to see an increase in body weight due to the influences of the food environment sector, regardless of the changes in physical activity.

6.2 Mental Well-Being Sector

The parameter changes in the Mental Well-being sector focus on the graphical functions. Due to the lack of evidence on the quantification of the relationship between variables within this sector, altering both the scale of the graphical functions as well as the shape of the curves can provide insight on whether or not a particular function serves as a leverage point for practitioners or policy makers.

Effect of PAL on Stress

The initial graphical function Effect of PAL on Stress takes into account the assumption that the effect of PAL on stress falls within a range of 0-2, indicating the lowest PAL value (1) provides an Actual Stress Level of 2, while a maximum value of PAL (2.5) provides an Actual Stress Value of 1 (which matches the initial value for the Normal Stress Level). The curve also assumes that any PAL value greater than the initial value (~1.15), the effect of PAL of Stress is equal to 1. This indicates that only a decrease in physical activity (from the initial value) would lead to a higher stress value.

A parameter test was conducted with the graphical function Effect of PAL on Stress. Two different curves were simulated. Figures 24 outlines the different curves used. Figures 25 and 26 provide the results of the simulation.
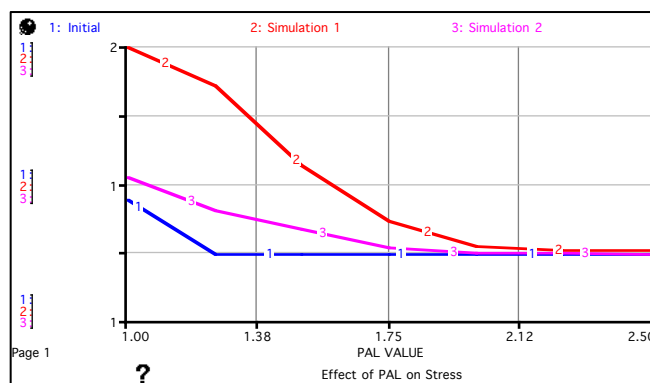
Figure 24: Sensitivity Analysis Mental Well-being Sector: Effect of PAL on Stress. The blue line indicates the initial graphical function curve, the red line the curve used in the second simulation, and the purple line, the curve used in the third simulation.

Figure 25: Sensitivity Analysis Mental Well-being Sector: Actual Stress. The blue line indicates the initial simulation result; the red line the second simulation result, and the purple line, the result of the third simulation.

Figure 26: Sensitivity Analysis Mental Well-being Sector: Actual Emotional Eating Level. The blue line indicates the initial simulation result; the red line the second simulation result, and the purple line, the result of the third simulation

The results shown in Figure 25 indicate a stable value for Actual Stress across all three different graphical functions. As one's PAL is the only variable influencing stress in the model, we would expect to see this behavioral pattern due to the minimal changes seen in PAL over time within the model. With an initial higher Actual Stress Level (as seen in simulations 2 and 3), we would expect to see a higher initial value for Actual Emotional Eating Level (as seen in Figure 24). The behavior seen in the Actual Emotional Eating Level exhibits a goal seeking behavior towards a value of 1. This is due to the Stress Ratio normalizing back to a value of 1 over time (due to the Normal Stress Level adapting to meet the Actual Stress Level). Analysis of the graphs indicates

that the higher the Actual Stress level, the greater initial value we see of the Actual Emotional Eating Level.

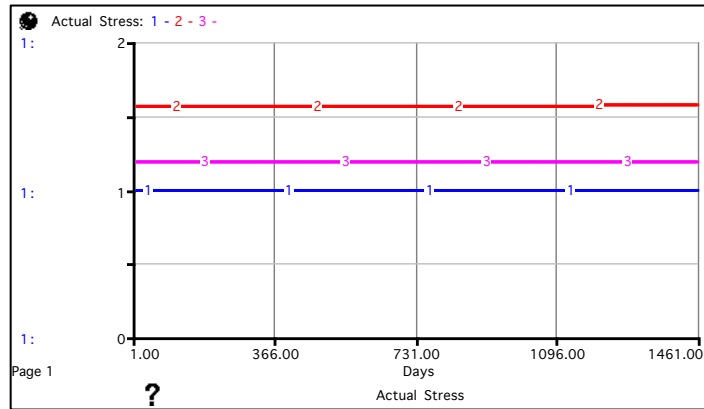**Figure 27: Sensitivity Analysis Mental Well-being Sector: Body Weight**. The blue line indicates the initial simulation result; the red line the second simulation result, and the purple line, the result of the third simulation.

Figure 27 highlights the changes in body weight seen through the simulation runs for the mental well-being sector sensitivity analysis. In the initial simulation, the initial PAL value was set to ~1.115 and resulted in an Actual Stress Value of 1. Any decrease in the initial value of the PAL (e.g. if it was initialized at 1.04), this value produces an Actual Stress Value greater than 1, thus creating discrepancy it creates between the Actual Stress Value and the Normal Stress Value. This discrepancy triggers the reinforcing loop that then drives works to increase energy intake through emotional eating and antidepressant use.

We see in the simulation 3 that even though the shape of the graphical function curve differs from that of the initial simulation, the curve in simulation three still provides an Actual Stress value of 1 when PAL is equal to 1.115, thus indicating no difference in the weight gain pattern when compared to the initial simulation run.   Overall we see that even with a three-fold increase in one's Actual Stress Level (From 1 to 3), we only see a minimal increase in one's body weight. This indicates that based upon the current model structure, one's stress level would not be recommended to policy makers as a leverage point for policies to improve the weight of Canadians.

Effect of Stress Ratio on Actual Emotional Eating Level

The current graphical function Effect of Stress Ratio on Emotional Eating takes into account the assumption that the Effect of the Stress Ratio on one's Actual Emotional Eating level falls within a range of 0-3. This indicates that a Stress Ratio value of less than or equal to 1 provides an output effect (an Actual Emotional Eating Level) of 1, indicating no effect on the Actual Emotional Eating Level, and a maximum value of the Stress Ratio (a value of 2) provides an output effect of 3.

A sensitivity analysis was conducted with the graphical function Effect of Stress Ratio on Actual Emotional Eating Level. Figures 28 outlines the different curves used.

Figure 28: Sensitivity Analysis Mental Well-being Sector: Effect of Stress Ratio on Actual Emotional Eating Level. The blue line indicates the initial simulation result; the purple line the second simulation result, and the green line, the result of the third simulation.

Figure 29 highlights the change seen in the Actual Emotional Eating Level based upon the change in the graphical function. We see that there is minimal change in simulation 1 from the initial value, however simulation 3 provides a greater change in the Actual Emotional Eating Level. As any value above 1 for the Actual Emotional Eating Level will trigger a response by the Emotional Eating Level Ratio to increase one's energy intake, we see in Figure 30 that simulation 3 provides a greater increase in weight over time.
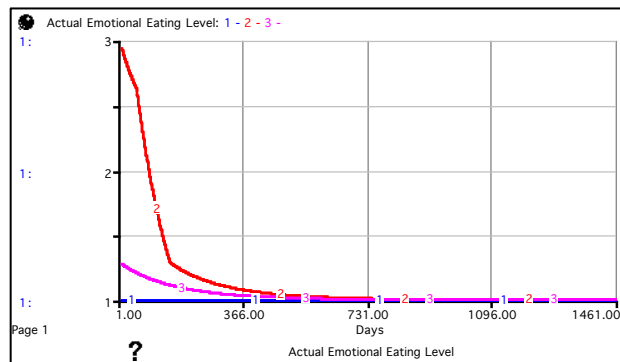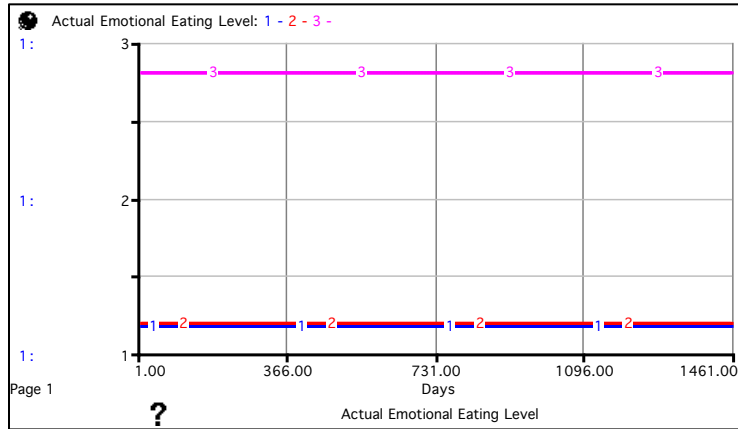
Figure 29: Sensitivity Analysis Mental Well-being Sector Actual Emotional Eating Level. The blue line indicates the initial simulation result; the purple line the second simulation result, and the green line, the result of the third simulation
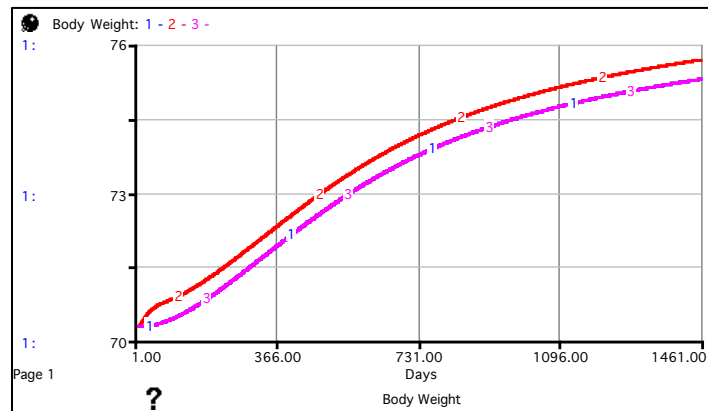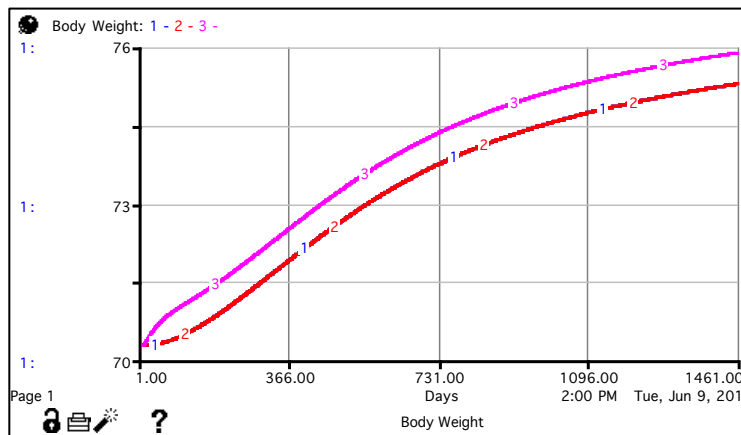

Figure 30: Sensitivity Analysis Mental Well-being Sector Body Weight. The blue line indicates the initial simulation result; the purple line the second simulation result, and the green line, the result of the third simulation.

6.3 Multiple Parameter Assessments

Previous sensitivity analysis of parameters has focused on altering a single parameter at a time to see the effects of weight. This section describes the model behavior based upon changing multiple parameters at one time. Table 13 provides information on the changes made in the model. Figure 31 provides the results of the multiple parameter changes.

Parameter	Initial Value	Simulation 2 Value	Simulation 3 Value	Simulation 4 Value
NEWS Rating	4	6	2	10
Ability to Engage in Physical Activity	1	3	0.5	5
Normal Stress Level	1	3	2	0.2
Normal Level of Emotional Eating	1	3	2	0.2
Potential Annual Income	$58500	$65000	$48000	$70000

Table 13: Multiple Parameter Assessments – Changed parameter values
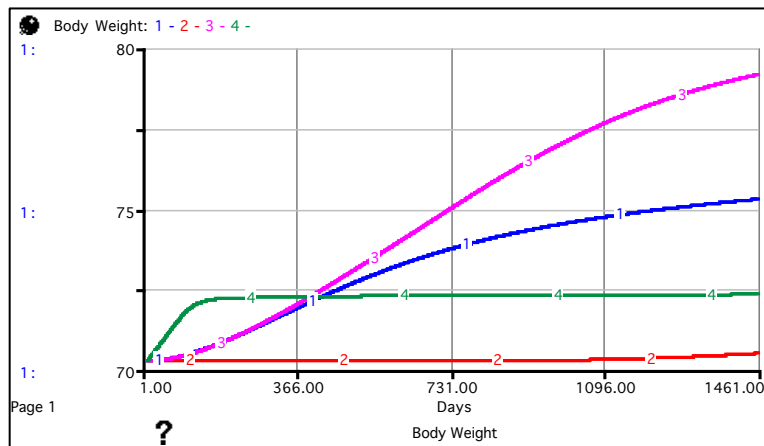
Figure 31: Multiple Parameter Changes – Body Weight. The blue line is the result from the initial simulation; the red line from simulation 2; the purple line from simulation 3; and the green line from simulation 4.

For Simulation 2, we see minimal change in weight, with the change coming after year three. As the parameter changes made increased the likelihood an individual would increase their physical activity, coupled with increasing the normal values for the mental well-being variables, thus reducing the strength of the reinforcing loops from the mental well-being sector that drive one's energy intake (via emotional eating and antidepressants), we would expect to see minimal increases in body weight. The increase

in body weight seen near the end of the simulation can be attributed to the increasing cost of purchasing healthy food, as the annual percent increase is greater than that of the potential income. Even though the Potential Annual Income is greater in simulation 2, eventually the rise in the Average Annual Cost of Purchasing Healthy Food becomes greater than the Actual Annual Income, thus increasing the Percentage of Annual Income Allocated for Food, increasing the potential difficulty in purchasing healthy foods.

For simulation 3, we see a greater overall increase in body weight, with the same behavioral pattern represented as in the initial simulation. In this simulation, the changes resulted in a decrease in the physical activity, thus reducing the impact of physical activity (PAL) on stress. The changes made to the mental well-being variables result in a weakening of the reinforcing loops that flow through the mental-well being sector, thus potentially offsetting some of the reinforcing effect seen from the reducing in physical activity. As the Potential Annual Income was reduced from the initial value, we see this as the major driver behind the increase in the body weight.

For simulation 4, the behavioral pattern differs from the initial simulation run. In this simulation, factors influencing physical activity were increased, thus reducing one's stress level and the strength of the reinforcing loops that are driven by stress. However, as the normal values for the mental well-being variables were reduced, this results in a strengthening of the same reinforcing loops that work to drive energy intake. The increase in Potential Annual Income works to offset the increase in energy intake seen via the mental well-being sector. The initial increase in weight can be attributed in large to the mental well-being sector, as both the Stress Ratio and Emotional Eating Ratio are at their largest values at the initial simulation, resulting in the strongest effect from both variables. As the Normal values eventually are increased to meet their actual counterparts, we see a reduction in their strengths and thus a reduction in the rate of weight gain. The stabilization of body weight can be attributed to two factors. First, as the aforementioned normal values adapt to meet their actual counterparts, we see their effects reduced to zero. Second, as the Actual Annual Income continues to be higher than in the initial simulation, we see no difficulties in purchasing healthy food, hence there is no effect increasing one's energy intake. As seen in simulation 2, the body weight

increase seen near the end of simulation 3 can be attributed to a greater rise in food costs in relation to a the rise in actual income.

7. Model Simulation Results – Prototype B Simulation

The previous sections discussed the initial simulation results and the results when a number of different model parameters were adjusted based upon the same prototype individual. One benefit of the model is that it can be calibrated for an infinite number of prototype individuals. This feature can be of use in particular to health care practitioners, whose learning may be improved by understanding not only the dynamics at play within the system, but also how these dynamics may change depending on the individual and the individual's environment.

The following section details the profile of a second prototype individual, including parameter changes and simulation results.   Table 14 compares the characteristics of Prototype B with the prototype individual ran in the initial simulation.

Characteristic	Prototype A	Prototype B
Age	41 years	50 years old
Sex	Male	Female
Weight	70.72kg	87.65kg
Height	1.69	1.66
BMI	24.76	32
Daily PA	24 minutes	10 minutes

Table 14: Comparison of Prototype A and Prototype B Parameters

In order to correctly adjust for the change in physical activity, further changes needed to be made in the physical activity sector in order to ensure an initial value of 0 for daily physical activity. There were a number of possible changes to make. For this simulation, it was selected to change the parameters Effect of Facilities on Time Used for Rec PA and Effect of NEWS on Time Used for Util PA. These two factors were changed instead of changing factors that influenced the flow Time Available for Leisure Activity

as it was assumed that the individual might still have the same amount of Leisure Time Available, however they can allocate it to non-Physical Activity Leisure Time (i.e. social or cognitive leisure activities).

Without changing any further parameters, the initial base run of prototype B shows a similar pattern of weight gain as with prototype A.
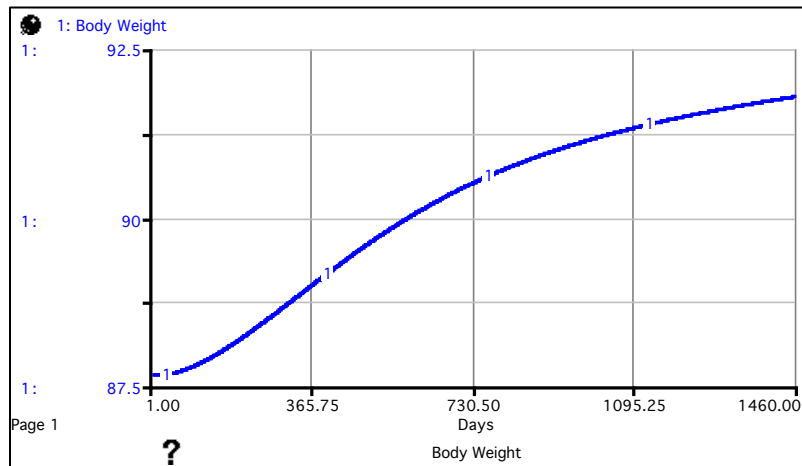
Figure 32: Prototype B simulation run: Body Weight

Table 15 shows the rate of weight gain, compared to that of prototype A.

Time Frame	End Weight (kg) – Prototype A	Percent Change – Prototype A	End Weight (kg) – Prototype B	Percent Change – Prototype B
Day 1	70.72	-	87.65	
Day 365	71.95	1.7%	89.02	1.6%
Day 730	73.79	2.6%	90.53	1.7%
Day 1095	74.77	1.3%	91.53	1.1%
Day 1460	75.32	0.7%	91.79	0.28%

Table 15: Comparison of Body Weight for Prototype A and Prototype B simulation results

The results from the initial simulation of prototype B indicate the weight gain falls within the acceptable range found in the NLYS study (27). Further parameters were changed to alter the profile of the prototype B individual. Table 16 outlines the changes. The results from the parameter changes for prototype B are presented in Figure 33.

Parameter	Prototype A	Prototype B
NEWS	4	2
Number of Facilities in Buffer Zone	2	6
Ability to Engage in Physical Activity	1	0.7
Normal Stress Level	1	0.6
Normal Emotional Eating Level	1	0.7
Potential Annual Income	$585000	$60000

Table 16: Comparison of parameter changes for test simulation of Prototype B.
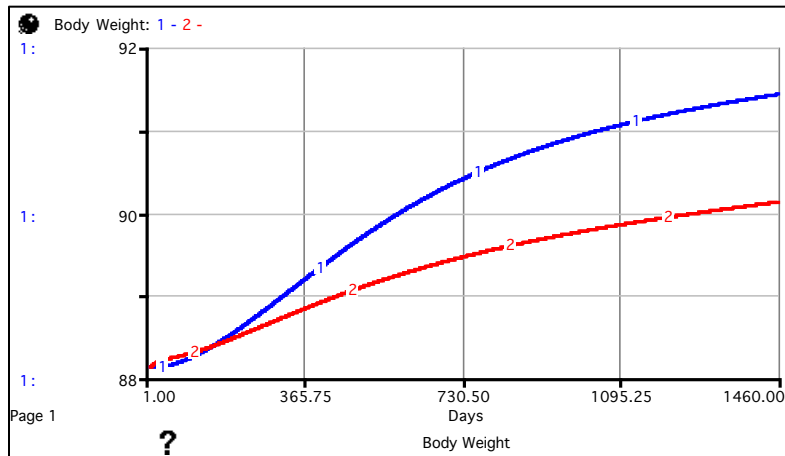
Figure 33: Multiple Parameter Changes Prototype B: Body Weight. The blue line indicates the initial simulation run for Prototype B; the red line the result of the parameter changes seen in Table 14.

Overall the behavior of weight gain in the second simulation (red) exhibits the same s-shaped growth pattern seen in the initial simulation. The initial increase in weight can be attributed to the mental well-being sector, as reducing the normal values for both Emotional Eating and Stress both trigger the reinforcing loops they encompass, thus

increasing one's intake. The physical activity sector works to reduce the effects seen by stress (As physical activity was initially increased), however due to the model's current formulation, we see that this increase in energy expenditure (via in increase in physical activity) also drives up the energy intake, thus providing a higher baseline value for the effects of emotional eating and stress to be multiplied against.

The realistic outputs seen through the simulation runs of Prototype B improve the validation of the model structure as a whole. As the model has the potential to be used by health care providers to help them gain insight on the influences over one's weight over time (both past and future), ensuring the model can provide plausible outputs for a second prototype individual proves to be key in ensuring the usefulness of the model.

8 Limitations

The results of the initial simulation model and subsequent validation and sensitivity tests indicate the current model structure is able to reproduce behavioral patterns in a number of variables that would be deemed plausible outputs in comparison to their real world counterparts. However, there are a number of opportunities for improvement of the model, both from a conceptual and a technical perspective. The following section will highlight these model limitations, providing insight on the limitations from a model as a whole, followed my limitations within each sector.

Conceptual Model Limitations

The initial goal of the thesis was to translate the CLD created by the PHSA into a stock and flow model using system dynamics methodology. Currently the model does not encompass all factors that were identified within the CLD. Although the model does include representation from four of the major sectors that influence weight, physical well being, and mental well being, without the full representation of all factors, the model is not able to provide its maximum benefit to both policy makers and health care practitioners. The model does still lend itself to providing a lens for systems thinking, providing both groups with new ways to consider how to collectively address complex

societal problems like obesity, where biology interacts with social, cultural and built environmental factors in infinite permutations and combinations. However as Finegood (91) states, the systems that give rise to the obesity epidemic function at multiple levels, and there are important interactions between these levels. Here it is vital that we understand all of these interactions. By not including all factors that play a role in the obesity system, this limits health care practitioners from not only gaining a full understanding of the system, but it also prevents them from providing the most specific, patient centered advice to clients who are struggling with their weight. For policy makers, the absence of factors not does enable a full understanding of all leverage points in the system. If this model was to be used by policy makers, it runs the risk of having policy makers implement policies that may not necessarily be the most efficient or effective policies to help improve the weight and well being on the population.

A second limitation of the model involves the lack of representation of individual decision-making. Currently the model does not account for any decision-making behaviour that takes into account an individual's desire to lose, gain, or maintain their current weight. As behaviour is a key component influencing one's health behaviours (92) not including such a factor renders the model less effective in portraying the real-life system of weight and well being.   As behaviour change has been identified as a critical piece of one's nutritional counselling by dietitians (93) (94), including factors representing individual decision making and behavioural change can serve as important parts of one's obesity and wellbeing system that a health care practitioner must take into account.

Two major limitations of the overall model step from the quantification process. First, the data currently populating the model is based upon an individual, not the population. Difficulties in accessing population data for such variables as the average number of facilities within a buffer zone or the average NEWS for a particular environment made calibrating the model to a population scope not possible. For policy makers, analyzing a population level model would prove to be more useful as the policies implemented would be aimed at improving the population as a whole, rather than one individual. In particular, the mental well-being sector includes a number of factors that

are calibrated based upon assumptions for an individual and therefore may not reflect the overall behaviour of the population with regards to some cause and effect relationships.

A second limitation concerning the quantification of the model refers to the operationalizing of variables. The PHSA CLD was composed of a number of soft variables or intangible variable, those that relate to attributes of human behaviour or effects those variations in such behaviour produce (95). These variables are difficult or even impossible to measure; yet their inclusion in a model is a matter of necessity as they are known to be a part of the causal relationship chain of a model (96). Finding real-world objective measures to operationalize such soft variables was not possible (i.e. emotional eating, perceived weight bias). In these cases the variables were included in the model as proxy variables and serve as areas to be developed further. Furthermore, as the system dynamics methodology relies on quantified direct causal relationships to build a simulation model, the initial starting point of the system dynamics model, the PHSA CLD, was not developed based upon published, quantified data of the relationships. Instead, this CLD was published using the insight from subject matter experts. Therefore the subject matter experts may have been correct in identifying the causal relationships, however published data is not yet available to support their expertise.

In the fortunate cases where operationalizing of the soft variables was possible (e.g. using NEWS to represent a number of the different factors representing the built environment), a further challenge was met with regards to quantifying the relationship between the variable and its counterpart in the causal relationship. Here, graphical functions were used to represent such a relationship. In order to produce a graphical function, a number of pieces of information are needed:

1. Range of values for the input variable
2. Range of values for the output of the effect
3. Shape of the curve representing the strength of the effect of the output at different levels of input.

The majority of the published literature on the relationships did not provide the results of the cause and effect relationship over a range of input (or cause) values. For example, the study by Erikkson et al. (59) who found that participants with more than four exercise facilities within their buffer zone spent on average 5.4 more minutes in

moderate to vigorous physical activity per day, compared to those with no exercise facilities within their buffer zones. This study however does not provide information on the increase seen if there are five or six exercises facilities within the buffer zone. One may assume that as the number of facilities increase, this also increases the amount of physical activity, however the rate of increase is unknown. In discussion with subject matter experts, experts from the built environment sector indicated the nature of such relationship would be in the form on s-shape curve (indicating a non-linear relationship), however the range of output variables was too difficult to determine. As the model includes a number of graphical functions, the lack of published data on these factors serves as a limitation to the model, and highlights a gap in the current research available.

In order to overcome such challenges in the future, one may wish to employ techniques such as using group model building scripts (i.e. parameterized relationship between two variables, ratio exercises) (97). Similar methods were applied in an attempt to capture the quantified nature of some causal relationships (physical activity, mental well-being). Subject matter experts where interviewed individually and were asked to provide information regarding the formulation of a graphical function. The experts were not able to provide the full range of data required for such a function to be built. Having the experts perform the tasks outlined in the scripts in a group setting may be more successful.

Physiology Sector Limitations

The current formulation of energy intake is based upon one's energy expenditure multiplied by the effects from the mental well-being and food environment sector. Conceptually, one's energy expenditure would influence one's energy intake if one were attempting to maintain an energy balance. However the current formulation of energy intake is incorrect. As the sensitivity analysis demonstrated that even with a drastic increase in physical activity one would gain weight at a higher rate over the same time frame, this formulation is not the most accurate representation of the real world. This formulation could prove true if the weight gained was solely fat free mass, however this is not the case in the model. One may have reformulated the energy intake to be grounded

by only the initial value of one's energy expenditure, thus uncoupling intake from expenditure through the span of the simulation. This formulation too would be incorrect as it could lead to a drastic weight loss in the model if the energy expenditure stayed at a higher level than one's intake over a long period of time.

A second limitation of the physiology section is the inability of the model to distinguish between the addition of fat mass and fat free mass. Currently the model allocated any weight gain as either fat mass or fat free mass using the energy-partitioning factor. This factor does not taken into consideration any physical activity completed, with the assumption being one's physical activity can alter the body weight through the gaining of fat free mass and loss of fat mass.

Physical Activity Sector Limitations

The limitations mentioned for the overall model in section 5.1 can be seen within the physical activity sector. These limitations have resulted in a reduced number of feedback loops flowing through the physical activity sector. Due to the reduced number of loops, there is limited dynamic behaviour displayed by the variables within the sector. This lack of loops is in part due to the fact that this sector is not fully developed (there are a number of factors within the PHSA CLD yet to be added). The lack of development within this sector does not enable the model to produce the best possible representation of the real world. As policy makers may be interested in this sector particularly for the opportunities that the built environment lend in terms of policy design, further development would needed on this sector to best enable policy makers to understand the true system at play.

Mental Well-Being Sector

The major challenge seen specifically within the mental well-being sector is similar to the challenge seen within the physical activity sector. The boundary for the mental well-being sector includes only a small number of factors influencing each variable, or in some cases, one a single causal relationship is depicted to influence a

variable. For example, one's level of depression is only influenced by stress and perceived weight bias. However a simple online search for causes of depression brings up a host of other factors that influence depression (98) For policy makers, these specific factors may not be as useful to include within the scope of the model as they may be too individual specific and may not be the focus of policy intervention. However for health care practitioners, such factors such as family history or substance abuse may be of interest to see how such factors influence weight and well-being.

Food Environment Sector Limitations

The behaviour seen in the initial simulation runs is in large part driven by the effects from the food environment sector. As there are a number of aspects of the food environment (99), this model only looks at the role of income. Expanding the model boundary to include other factors from the CLD such as availability of healthy foods and the effect of food marketing would improve the portrayal of the food environment sector. Such an expansion would also help overcome the limitation seen in the effect of the Percentage of Annual Income Allocated for Food. As the effect was derived to produce demonstrates a high level of sensitivity to very small changes in the Percentage of Annual Income Allocated for Food ratio, it is highly unlikely to see such sensitivity in the real world. For example, a 2% change in one's annual income needed to be allocated for food would not produce a change in purchasing behaviour, unless the percentage change was based upon a lower income level where a 2% change could have consequences on other household spending.

9 Future Work

The simulation results highlighted the model structure's ability to produce a plausible behavior in terms change in one's body weight over time. However a number of limitations to the model were identified, along with recommendations to overcome the limitations. This section provides further insight into one of the limitations and offers a more in-depth discussion on potential solutions.

Although the current model structure is calibrated based upon individual characteristics, it currently does not take into account an individual's own motivations or decision-making ability to obtain a particular body weight. Both studies and practitioners have identified the role individual motivation plays in one's weight management journey. (100) (101). Both internal motivation to lose weight and self-motivation have been identified as predictors of successful weight control. Dietitians have identified that their role in aiding clients in their weight management journey involves more than filling a knowledge gap with regards to what a client needs to eat to achieve their goals. Moving from the role of an expert to that of a coach, dietitians have focused on including motivation interviewing techniques as a method to help overcome a lack of motivation in clients that has been found to be cause for poor adherence to weight management programs (101). There are a number of different motivational theories that have been researched regarding weight management, including the self-determination theory (101), the social cognitive theory, the transtheoretical model, the theory of planned behaviour (102). These theories will not be discussed, however are presented to highlight the variety in change theories that have been linked to weight management.

A recommendation going forward is to include a motivation factor within the model. The current model structure offers a number of potential opportunities to influence one's motivation. Figure 33 offers one possible framework for including motivation within the current model
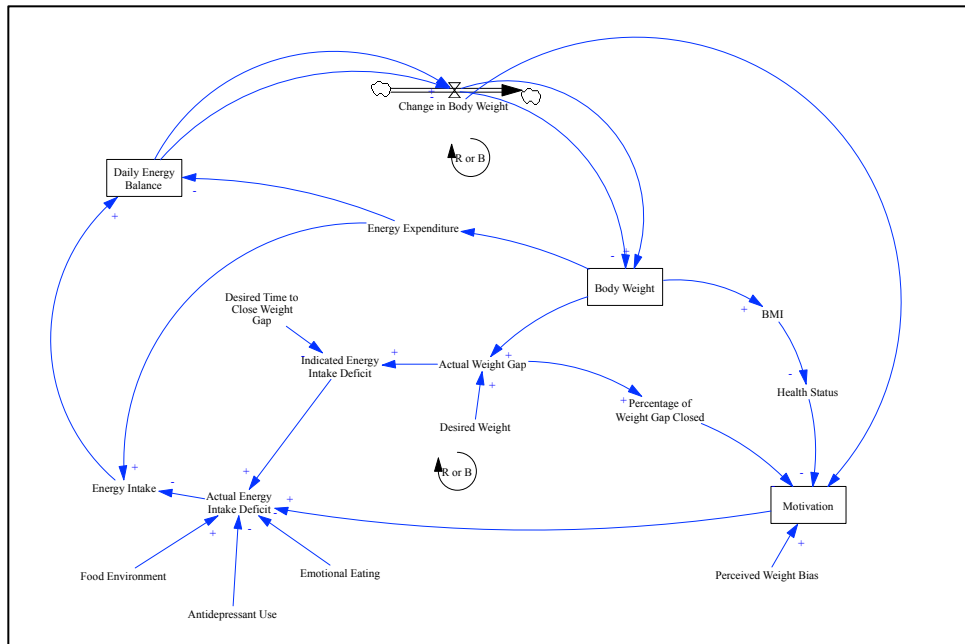
Figure 33: Possible addition to current simulation model

This causal loop diagram takes into consideration the effect of motivation on achieving a particular weight target. This diagram requires an individual to make a decision regarding their weight – whether they wish to maintain their current weight, gain, or lose weight. Based upon their decision and the time in which they hope to achieve such a desired weight, this provides a daily energy deficit (Indicated Energy Intake Deficit). This structure mimics that normally seen in real life weight loss settings, as clients are often provided with an intake goal based upon their estimated energy expenditure. This energy deficit goal would be influenced by a number of factors, including the three factors currently influencing energy intake, as well as an additional motivation factor. Here, motivation would play a role in how able one is to achieve their target energy deficit (or energy intake). Motivation itself has the potential to be influenced by a number of factors, such as one's perceived weight bias and their health status. Furthermore, one's motivation is driven by one's goal itself. As one gets closer and closer to achieving their particular weight goal, this often serves as a negative influence in motivation itself due to burnout.

Additional of this structure to the model is important if the model is going to be used by health care practitioners to enable them to gain a more patient centered approach to understanding the factors influencing their patient's weight loss journey. From a

policy maker standpoint, understanding the role of motivation from an individual standpoint may not add additional value to their use of the model. For policy makers, future work needs to focus on two key factors. First, adding the remaining factors from the PHSA CLD is critical to provide policy makers with the complete picture of the weight and well-being system. Second, as the weakest piece in terms of quantification of the model stems from the development of the graphical functions, hosting additional conversations with subject matter experts will be important in order to increase the model's validity to better match that of the real world system.

The benefits of the system dynamics model have the potential to extend beyond the use of policy makers and health care practitioners to both health care students as well as clients themselves. For students, having an interactive tool such as a system dynamics model lends itself to not only aiding in the understanding of the obesity system, but also provides them with a safe environment to test different patient scenarios to see how different care plans work to provide different results depending on patient characteristics. For clients, this model can also serve an education purpose. By discussing with a health care provider the numerous factors that play a role in one's weight and well-being (regardless of the extent to which these factors apply to him/her specifically) the model can create a dialogue about the complexity of weight and well-being, and also to engage the patient in helping identify their story within the model. In doing so, it can help shift away from the shame and blame game often clients feel and help them understand the role of the system on their weight management challenges (103).

10 Conclusion

An initial glance of the Foresight Map or the PHSA CLD and the imagery of a complex, messy system is brought to light. With the large number of variables, causal linkages, and feedback loops at play, such maps raise questions of not only regarding the "what" (as in what factors are included) but also the "how" - how such factors interact to cause change in the system. The aim of the system dynamics model created was to identify how the dynamic interactions between socio-economical and physical environmental factors affected an individual's physical well-being, mental well being,

and weight. The model accomplished this through by translating pieces of the PHSA CLD into a simulation modeling using system dynamics methodology.

The results of the simulation model demonstrated that the interactions between physical activity, mental well-being, the food environment, and one's physiology within the current model structure could produce a change in body weight similar to that seen in a longitudinal study on weight gain. Furthermore, the behavioral pattern also matches the pattern of weight gain seen in British Columbia residents, and Canadians, over the past decade. Due to the nature of the results indicate that the current model structure can serve as one dynamic hypothesis describing how the problematic behavior (weight gain) arose over time. Although the model currently does not include all the factors from the CLD, representation from the four major sectors allows for an increase in confidence in terms of the model's ability to accurately represent its real world system counterpart.

As the area of obesity is not merely complicated, but complex, the model serves as both an educational tool to help policy makers and health care practitioners understand the complex system and as well, as a tool to help improve the work of both parties. For health care practitioners, gaining a better understanding of the system at play that is influencing their client's weight and well-being. For policy makers, having the opportunity to identify leverage points within the system where policy changes can make an important enables them to make smarter decisions. Furthermore, having the opportunity to test such policies in a safe environment as within a system dynamics model provides additional benefits as it increases the probability that the policies will produce the intended benefits, and it also provides policy makers with an idea of just how much change is needed to achieve a particular result, and how the performance indicators (variables) improve over time, taking into account the state of the system and its delays.

The limitations identified in the model not only serve as a seed for future improvements to the model itself, but also have implications for within the system dynamics community. First, as the work on obesity within the system dynamics community has focused on building models of only a small number of pieces of the overall system, this model is one of the first to address a broader range of factors influencing not only weight, but also its links to physical and mental well-being. Second, the model flags a number of challenges that future system dynamicists will face in

continuing within this field - particularly surrounding the operationalizing of soft variables and the creation of the graphical function. The thesis works to fill a gap not only with regards to the aforementioned lack of system dynamics of the full obesity and well-being system, but to also address the current gap in research regarding how variables and relationships are measured. The lack of data on the non-linear relationships should be of major concern for policy makers and health care practitioners as it is this concept is critical in their planning of interventions, whether at a population or an individual level.

11 REFERENCES

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12 APPENDIX A

The model is enclosed in a CD-ROM. The following pages provide the complete model documentation generated by the iThink software. The documentation includes the equations, initial and parameter values, units, as well as graphical functions specifications.

A. Stocks and Flows:

Energy_Balance(t) = Energy_Balance(t - dt) + (Energy_Intake - Energy_Balance__to_Fat_Mass - Energy_Expenditure - Energy_Balance_to__Fat_Free_Mass) * dt
INIT Energy_Balance = 0
UNITS: kilocalorie

>　INFLOWS:
>　Energy_Intake = Energy_Expenditure*Effect_on_Energy_Intake
>　UNITS: kcal/day

>　OUTFLOWS:
>　Energy_Balance__to_Fat_Mass = ((1-Energy_Partitioning_Factor)*Energy_Balance)/Adjustment_time__EB_to_FM
>　UNITS: kcal/day

>　Energy_Expenditure =
>　(Constant+RMR_Fat_Mass+RMR_Fat_Free_Mass+(Physical_Activity__Coeffici
>　ent*Body_Weight)+(Adaptive_thermogenesis__parameter*Change_in__Energy_
>　Intake)+(Change_in_Fat_Mass*Energy_cost_for__FM_Deposition)+(Change_in_
>　Fat_Free_Mass*Energy_cost_for__FFM_Deposition))
>　UNITS: kcal/day

>　Energy_Balance_to__Fat_Free_Mass =
>　(Energy_Partitioning_Factor*Energy_Balance)/Adjustment_time__EB_to_FFM
>　UNITS: kcal/day

Average_Annual_Cost_of_Purchasing_Healthy_Food(t) = Average_Annual_Cost_of_Purchasing_Healthy_Food(t - dt) + (Change_in_Average_Annual_Cost_of_Purchasing_Healthy_Food) * dt
>　INIT Average_Annual_Cost_of_Purchasing_Healthy_Food = 7853.52
>　UNITS: Canadian Dollars (CAD)

>　INFLOWS:

Change_in_Average_Annual_Cost_of_Purchasing_Healthy_Food =
((Annual_Food_Cost__Inflation*Average_Annual_Cost_of_Purchasing_Healthy
_Food+Average_Annual_Cost_of_Purchasing_Healthy_Food)-
Average_Annual_Cost_of_Purchasing_Healthy_Food)/Time_to_Change_Averag
e_Annual_Cost
UNITS: cad/day

Barriers_to_Engaging__in_PA(t) = Barriers_to_Engaging__in_PA(t - dt) +
(Change_in_Barrier_to_Engaging_in_PA) * dt
INIT Barriers_to_Engaging__in_PA = 0.2
UNITS: Level of Fear (Fear)

    INFLOWS:
    Change_in_Barrier_to_Engaging_in_PA =
    ((1/2*Effect_of_Framingham_Risk_Score_on_Barrier_to_Engaging_in_PA+1/2*
    Effect_of_Weight_Bias_on_Barrier_to_Engaging_in_PA)-
    Barriers_to_Engaging__in_PA)
    UNITS: fear/day

Body_Weight(t) = Body_Weight(t - dt) + (Change_in_Body_Weight) * dt
INIT Body_Weight = 70.27
UNITS: kilogram

    INFLOWS:
    Change_in_Body_Weight = (Change_in_Fat_Mass+Change_in_Fat_Free_Mass)
    UNITS: kg/day

Fat_Free_Mass(t) = Fat_Free_Mass(t - dt) + (Change_in_Fat_Free_Mass) * dt
INIT Fat_Free_Mass = 56.03
UNITS: kilogram

    INFLOWS:
    Change_in_Fat_Free_Mass =
    (Energy_Balance_to__Fat_Free_Mass/Energy_Density_Fat__Free_Mass)
    UNITS: kg/day

Fat_Mass(t) = Fat_Mass(t - dt) + (Change_in_Fat_Mass) * dt
INIT Fat_Mass = 14.69
UNITS: kilogram

    INFLOWS:
    Change_in_Fat_Mass =
    Energy_Balance__to_Fat_Mass/Energy_Density__Fat_Mass
    UNITS: kg/day

Leisure_Time_Available(t) = Leisure_Time_Available(t - dt) +
(Time_Available_for_Leisure_Activity - Daily_Recreational_Physical_Activity -
Daily_Utilitarian_Physical_Activity - Non_Physical_Activity_Leisure_Time) * dt
INIT Leisure_Time_Available =
Percentage_of_Free_time_allocated_for_physical_activity*Free_Time_Available
UNITS: minutes (min)

    INFLOWS:
    Time_Available_for_Leisure_Activity =
    (Free_Time_Available*Percentage_of_Free_time_allocated_for_physical_activity
)/Time_to_Update__Leisure_Activity
    UNITS: min/day

    OUTFLOWS:
    Daily_Recreational_Physical_Activity =
    (Effect_of_Facilities_on_Desired_Time_Used_for_Rec_PA*Leisure_Time_Avail
    able)/Time_to_Update_Daily_Rec_PA
    UNITS: min/day
    Daily_Utilitarian_Physical_Activity =
    (Leisure_Time_Available*Effect_of_NEWS_on_Desired_Time_Used_for_Util_P
    A)/Time_to_Update_Daily_Util_PA
    UNITS: min/day
    Non_Physical_Activity_Leisure_Time = Leisure_Time_Available-
    Daily_Utilitarian_Physical_Activity-Daily_Recreational_Physical_Activity
    UNITS: min/day

Normal_Antidepressant_Use(t) = Normal_Antidepressant_Use(t - dt) +
(Change_in_NAU) * dt
INIT Normal_Antidepressant_Use = 1
UNITS: Unitless

    INFLOWS:
    Change_in_NAU = (Antidepressant_Use-
    Normal_Antidepressant_Use)/Time_to_Adjust_Normal_Antidepressant_Use
    UNITS: per day (1/day)

Normal_Level_of__Emotional_Eating(t) = Normal_Level_of__Emotional_Eating(t -
dt) + (Change_in_Normal_Emotional_Eating_Level) * dt
INIT Normal_Level_of__Emotional_Eating = 1
UNITS: Unitless

    INFLOWS:
    Change_in_Normal_Emotional_Eating_Level =
    (Actual_Emotional_Eating_Level-
    Normal_Level_of__Emotional_Eating)/Time_to_Update_Normal_Emot_Eating_
    Level

UNITS: per day (1/day)

Normal_Percentage_of_Annual_Income_Spent_on_Food(t) =
Normal_Percentage_of_Annual_Income_Spent_on_Food(t - dt) +
(Change_in_Normal_Percentage) * dt
INIT Normal_Percentage_of_Annual_Income_Spent_on_Food = 0.129
UNITS: Unitless

    INFLOWS:
    Change_in_Normal_Percentage =
    (Percentage_of_Annual_Income_allocated_for_food-
    Normal_Percentage_of_Annual_Income_Spent_on_Food)/TIme_to_Update_Nor
    mal_Percentage
    UNITS: per day (1/day)

Normal_Stress_Level(t) = Normal_Stress_Level(t - dt) +
(Change_in_Normal_Stress_Level) * dt
INIT Normal_Stress_Level = 1
UNITS: Unitless

    INFLOWS:
    Change_in_Normal_Stress_Level = (Actual_Stress-
    Normal_Stress_Level)/Time_to_Update_Normal_Stress_Level
    UNITS: per day (1/day)

Potential_Annual_Income(t) = Potential_Annual_Income(t - dt) +
(Change_in_Potential_Annual_Income) * dt
INIT Potential_Annual_Income = 58500
UNITS: Canadian Dollars (CAD)

    INFLOWS:
    Change_in_Potential_Annual_Income =
    (Potential_Annual_Income+(Annual_Salary_Inflation*Potential_Annual_Income)
    -Potential_Annual_Income)/Time_to_Change_Potential_Annual_Salary
    UNITS: cad/day

RMR_Fat_Free_Mass(t) = RMR_Fat_Free_Mass(t - dt) + (Change_in_RMR_FFM) *
dt
INIT RMR_Fat_Free_Mass = (22*56.03)
UNITS: kilocalories (kcal)

    INFLOWS:
    Change_in_RMR_FFM = (Fat_Free_Mass*RMR_Coefficient_FFM)-
    RMR_Fat_Free_Mass
    UNITS: kcal/day

RMR_Fat_Mass(t) = RMR_Fat_Mass(t - dt) + (Change_in_RMR__Fat_Mass) * dt
INIT RMR_Fat_Mass = 3.2*14.69
UNITS: kilocalories (kcal)

       INFLOWS:
       Change_in_RMR__Fat_Mass = (Fat_Mass*RMR_Coefficient_FM)-
       RMR_Fat_Mass
       UNITS: kcal/day

B. Variables and Parameters

Ability_to_Engage_in_PA = 1
UNITS: Unitless

Ability_to_Engage__in_PA_ratio =
Ability_to_Engage_in_PA/Normal_Ability_to_Engage_in_PA
UNITS: Unitless

Actual_Annual_Income =
Effect_of_Perceived_Weight_Bias_on_Income_Level*Potential_Annual_Income
UNITS: Canadian Dollars (CAD)

Actual_Depression_Level =
(1/2*Maximum_Level_of_Depression*Effect_of_Stress_Ratio_of_Depression)+(1/2*Maximum_Level_of_Depression*Effect_of_Perceived_Weight_Bias_on_Depression)
UNITS: Unitless

Actual_Effect_of_Antidepressant_Use_of_Energy_Intake =
SMTH1(Target_Effect_of_Antidepressant_Use_Ratio_on_Energy_Intake,365/2,1)
UNITS: Unitless

Actual_Effect_of_Easbility_of_Purchasing_Healthy_foods_in_Intake =
(SMTH1(Target_Effect_of_Income_ratio_on_ease_of_purchasing_healthy_foods,365/2,1))
UNITS: Unitless

Actual_Effect_of_Emotional_Eating_on_Energy_Intake =
Target_FX_of_Emotional_Eating_on_Energy_Intake
UNITS: Unitless

Actual_Emotional_Eating_Level = Effect_of_Stress_Ratio_on_Emotional_Eating
UNITS: Unitless

Actual_Stress = Effect_of_PAL_on_Stress
UNITS: Unitless

Adaptive_thermogenesis__parameter = 0.24
UNITS: Unitless

Adjustment_time__EB_to_FFM = 1
UNITS: days (day)

Adjustment_time__EB_to_FM = 1
UNITS: days (day)

Annual_Food_Cost__Inflation = 0.044
UNITS: Canadian Dollars-yr/yr

Annual_Salary_Inflation = 0.032
UNITS: Unitless

Antidepressant_Use = Effect_of_Depression_on_Antideprsssant_Use
UNITS: Unitless
Antidepressant_Use_Ratio = Antidepressant_Use/Normal_Antidepressant_Use
UNITS: Unitless

Barrier_of_Engaging__in_Phyical_Activity_Ratio =

Barriers_to_Engaging__in_PA/Normal_Barrier_of__Engaging_in_PA
UNITS: Unitless

Body_Mass_Index = Body_Weight/(Height*Height)
UNITS: kg/square meters

Change_in__Energy_Intake =
Change_in_Body_Weight*Energy_Intake_Change__Constant_A+(INIT(Body_Weight)-
Body_Weight)*Energy_Intake_Change__Constant_B
UNITS: kilocalories/day

Constant = 370.21
UNITS: kilocalories/day

Daily_Physical_Activity =
Daily_Utilitarian_Physical_Activity+Daily_Recreational_Physical_Activity
UNITS: minutes/day

Effect_of_Ability_to_Engage_in_PA_on_PA =
GRAPH(Ability_to_Engage__in_PA_ratio)
(0.00, 0.00), (1.00, 0.2), (2.00, 1.63), (3.00, 2.00)
UNITS: Unitless

Effect_of_Barriers_Engaging_in_PA_on_PA =
GRAPH(Barrier_of_Engaging__in_Phyical_Activity_Ratio)
(0.00, 1.00), (0.5, 0.807), (1.00, 0.2), (1.50, 0.141), (2.00, 0.0868), (2.50, 0.045), (3.00, 0.00), (3.50, 0.00), (4.00, 0.00), (4.50, 0.00), (5.00, 0.00)
UNITS: Unitless

Effect_of_BMI_on_Perceived_Weight_Bias = GRAPH(Body_Mass_Index)
(18.0, 0.00), (19.0, 0.00), (20.0, 0.00), (21.0, 0.00), (22.0, 0.00), (23.0, 0.00), (24.0, 0.00), (25.0, 0.103), (26.0, 0.116), (27.0, 0.138), (28.0, 0.145), (29.0, 0.167), (30.0, 0.183), (31.0, 0.19), (32.0, 0.215), (33.0, 0.235), (34.0, 0.273), (35.0, 0.338), (36.0, 0.428), (37.0, 0.498), (38.0, 0.63), (39.0, 0.765), (40.0, 0.897)
UNITS: Unitless

Effect_of_Depression_on_Antideprsssant_Use = GRAPH(Actual_Depression_Level)
(0.00, 1.00), (1.00, 1.00), (2.00, 1.00), (3.00, 1.00), (4.00, 1.00), (5.00, 1.00), (6.00, 1.00), (7.00, 1.00), (8.00, 1.00), (9.00, 1.00), (10.0, 1.00), (11.0, 1.00), (12.0, 1.00), (13.0, 1.00), (14.0, 1.00), (15.0, 1.00), (16.0, 1.00), (17.0, 1.00), (18.0, 1.00), (19.0, 1.00), (20.0, 1.50), (21.0, 1.50), (22.0, 1.50), (23.0, 1.50), (24.0, 1.50), (25.0, 1.50), (26.0, 1.50), (27.0, 1.50), (28.0, 1.50), (29.0, 2.00), (30.0, 2.00), (31.0, 2.00), (32.0, 2.00), (33.0, 2.00), (34.0, 2.00), (35.0, 2.00), (36.0, 2.00), (37.0, 2.00), (38.0, 2.00), (39.0, 2.00), (40.0, 2.00), (41.0, 2.00), (42.0, 2.00), (43.0, 2.00), (44.0, 2.00), (45.0, 2.00), (46.0, 2.00), (47.0, 2.00), (48.0, 2.00), (49.0, 2.00), (50.0, 2.00), (51.0, 2.00), (52.0, 2.00), (53.0, 2.00), (54.0, 2.00), (55.0, 2.00), (56.0, 2.00), (57.0, 2.00), (58.0, 2.00), (59.0, 2.00), (60.0, 2.00), (61.0, 2.00), (62.0, 2.00), (63.0, 2.00)
UNITS: Unitless

Effect_of_Facilities_on_Desired_Time_Used_for_Rec_PA =
GRAPH(Number_of_Facilities_in_Buffer_Zone_Ratio)
(0.00, 0.0804), (1.00, 0.138), (2.00, 0.183), (3.00, 0.209), (4.00, 0.293), (5.00, 0.437), (6.00, 0.556), (7.00, 0.817), (8.00, 0.939), (9.00, 1.00), (10.0, 1.00)
UNITS: Unitless

Effect_of_Framingham_Risk_Score_on_Barrier_to_Engaging_in_PA =
GRAPH(Framingham_Risk_Score)
(0.00, 0.333), (1.00, 0.333), (2.00, 0.333), (3.00, 0.333), (4.00, 0.333), (5.00, 0.333), (6.00, 0.34), (7.00, 0.35), (8.00, 0.357), (9.00, 0.368), (10.0, 0.374), (11.0, 0.383), (12.0, 0.391), (13.0, 0.415), (14.0, 0.434), (15.0, 0.466), (16.0, 0.496), (17.0, 0.531), (18.0, 0.627), (19.0, 0.733), (20.0, 0.867), (21.0, 1.00), (22.0, 1.00), (23.0, 1.00), (24.0, 1.00), (25.0, 1.00), (26.0, 1.00), (27.0, 1.00), (28.0, 1.00), (29.0, 1.00), (30.0, 1.00)
UNITS: Unitless

Effect_of_NEWS_on_Desired_Time_Used_for_Util_PA = GRAPH(NEWS_Rating)
(0.00, 0.00643), (1.00, 0.00643), (2.00, 0.0257), (3.00, 0.0611), (4.00, 0.181), (5.00, 0.28), (6.00, 0.333), (7.00, 0.437), (8.00, 0.495), (9.00, 0.524), (10.0, 0.54)
UNITS: Unitless

Effect_of_PAL_on_Physical_Activity_Coefficient = GRAPH(PAL)
(0.00, 1.00), (0.2, 1.00), (0.4, 1.00), (0.6, 1.00), (0.8, 1.00), (1.00, 1.00), (1.20, 1.33),
(1.40, 1.66), (1.60, 2.03), (1.80, 2.57), (2.00, 2.88), (2.20, 2.88), (2.40, 2.88), (2.60, 2.88)
UNITS: Unitless

Effect_of_PAL_on_Stress = GRAPH(PAL)
(0.00, 2.00), (0.0806, 2.00), (0.161, 2.00), (0.242, 1.98), (0.323, 1.95), (0.403, 1.92),
(0.484, 1.88), (0.565, 1.84), (0.645, 1.72), (0.726, 1.53), (0.806, 1.42), (0.887, 1.32),
(0.968, 1.19), (1.05, 1.13), (1.13, 1.00), (1.21, 1.00), (1.29, 1.00), (1.37, 1.00), (1.45,
1.00), (1.53, 1.00), (1.61, 1.00), (1.69, 1.00), (1.77, 1.00), (1.85, 1.00), (1.94, 1.00), (2.02,
1.00), (2.10, 1.00), (2.18, 1.00), (2.26, 1.00), (2.34, 1.00), (2.42, 1.00), (2.50, 1.00)
UNITS: Unitless

Effect_of_Perceived_Weight_Bias_on_Depression = GRAPH(Perceived_Weight_Bias)
(0.00, 0.0149), (0.1, 0.0532), (0.2, 0.115), (0.3, 0.169), (0.4, 0.213), (0.5, 0.244), (0.6,
0.26), (0.7, 0.273), (0.8, 0.286), (0.9, 0.29), (1.00, 0.29)
UNITS: Unitless
Effect_of_Perceived_Weight_Bias_on_Income_Level =
GRAPH(Perceived_Weight_Bias)
(0.00, 0.974), (0.05, 0.987), (0.1, 0.987), (0.15, 0.987), (0.2, 0.987), (0.25, 0.987), (0.3,
0.984), (0.35, 0.984), (0.4, 0.984), (0.45, 0.981), (0.5, 0.977), (0.55, 0.971), (0.6, 0.965),
(0.65, 0.955), (0.7, 0.945), (0.75, 0.939), (0.8, 0.932), (0.85, 0.923), (0.9, 0.907), (0.95,
0.887), (1.00, 0.887)
UNITS: Unitless

Effect_of_Stress_Ratio_of_Depression = GRAPH(Stress_Ratio)
(0.00, 0.0836), (0.5, 0.183), (1.00, 0.267), (1.50, 0.367), (2.00, 0.572), (2.50, 0.695),
(3.00, 0.823), (3.50, 0.9), (4.00, 0.952), (4.50, 0.968), (5.00, 0.974)
UNITS: Unitless

Effect_of_Stress_Ratio_on_Emotional_Eating = GRAPH(Stress_Ratio)
(0.00, 1.00), (0.2, 1.00), (0.4, 1.00), (0.6, 1.00), (0.8, 1.00), (1.00, 1.00), (1.20, 1.29),
(1.40, 2.63), (1.60, 3.00), (1.80, 3.00), (2.00, 3.00)
UNITS: Unitless

Effect_of_Weight_Bias_on_Barrier_to_Engaging_in_PA =
GRAPH(Perceived_Weight_Bias)
(0.00, 0.0611), (0.05, 0.067), (0.1, 0.0965), (0.15, 0.18), (0.2, 0.277), (0.25, 0.502), (0.3,
0.739), (0.35, 0.894), (0.4, 0.963), (0.45, 0.988), (0.5, 0.996), (0.55, 0.996), (0.6, 0.996),
(0.65, 0.996), (0.7, 0.996), (0.75, 0.996), (0.8, 0.996), (0.85, 0.996), (0.9, 0.996), (0.95,
0.996), (1.00, 0.996)
UNITS: Unitless

Effect_on_Energy_Intake =
(1/3*Actual_Effect_of_Emotional_Eating_on_Energy_Intake)+(1/3*Actual_Effect_of_A

ntidepressant_Use_of_Energy_Intake)+(1/3*Actual_Effect_of_Easbility_of_Purchasing_
Healthy_foods_in_Intake)
UNITS: Unitless

Emotional_Eating_Ratio =
(Actual_Emotional_Eating_Level/Normal_Level_of__Emotional_Eating)
UNITS: Unitless

Energy_cost_for__FFM_Deposition = 230
UNITS: kilocalorie/kilogram

Energy_cost_for__FM_Deposition = 180
UNITS: kilocalorie/kilogram

Energy_Density_Fat__Free_Mass = 1800
UNITS: kilocalorie/kilogram

Energy_Density__Fat_Mass = 9400
UNITS: kilocalorie/kilogram

Energy_Intake_Change__Constant_A = 9100
UNITS: kcal/kg

Energy_Intake_Change__Constant_B = 22
UNITS: Kcal/kg/day (kcal/kg-day)

Energy_Partitioning_Factor =
Forbes_body_composition_parameter/(Forbes_body_composition_parameter+Fat_Mass)
UNITS: Unitless

Forbes_body_composition_parameter =
(10.4*(Energy_Density_Fat__Free_Mass/Energy_Density__Fat_Mass))
UNITS: Unitless

Framingham_Risk_Score = 1
UNITS: Unitless

Free_Time_Available = 5.5*60
UNITS: minutes (min)
DOCUMENT: 5.5 hours - stat from 2009 "Time Spent Study"

Height = 1.69
UNITS: meters (m)

Maximum_Level_of_Depression = 63
UNITS: Unitless

NEWS_Rating = 4
UNITS: Unitless

Normal_Ability_to_Engage_in_PA = 1
UNITS: Unitless

Normal_Barrier_of__Engaging_in_PA = 0.2
UNITS: Level of Fear (Fear)

Normal_Number_of_Facilities_within_Buffer_Zone = 1
UNITS: Rec Facilities (RecFacilities)

Normal_Physical_Activity_Coefficient = 7
UNITS: Kcal/kg/day (kcal/kg-day)

Number_of_Facilities_in_Buffer_Zone_Ratio =
Number_of_Facilities_within_Buffer_Zone/Normal_Number_of_Facilities_within_Buffe
r_Zone
UNITS: Unitless

Number_of_Facilities_within_Buffer_Zone = 2
UNITS: Rec Facilities (RecFacilities)

PAL = PAL_point_per_minute_of_moderate_PA
UNITS: Unitless

PAL_point_per_minute_of_moderate_PA = GRAPH(Daily_Physical_Activity)
(0.00, 1.00), (30.0, 1.20), (60.0, 1.50), (90.0, 1.60), (120, 1.70), (150, 1.95), (180, 2.20),
(210, 2.20)
UNITS: Unitless

Perceived_Weight_Bias = SMTH1(Effect_of_BMI_on_Perceived_Weight_Bias,365/2)
UNITS: Unitless

Percentage_of_Annual_Income_allocated_for_food =
Average_Annual_Cost_of_Purchasing_Healthy_Food/Actual_Annual_Income
UNITS: Unitless

Percentage_of_Annual_Income_Allocated_for_Food_Ratio =
Percentage_of_Annual_Income_allocated_for_food/Normal_Percentage_of_Annual_Inc
ome_Spent_on_Food
UNITS: Unitless

Percentage_of_Free_time_allocated_for_physical_activity =
(Effect_of_Barriers_Engaging_in_PA_on_PA)*(1/2)+(1/2)*(Effect_of_Ability_to_Enga
ge_in_PA_on_PA)
UNITS: Unitless

Physical_Activity__Coefficient =
Effect_of_PAL_on_Physical_Activity_Coefficient*Normal_Physical_Activity_Coefficie
nt
UNITS: Kcal/kg/day (kcal/kg-day)

RMR_Coefficient_FFM = 22
UNITS: Kcal/kg/day (kcal/kg-day)

RMR_Coefficient_FM = 3.2
UNITS: Kcal/kg/day (kcal/kg-day)

Stress_Ratio = Actual_Stress/Normal_Stress_Level
UNITS: Unitless

Target_Effect_of_Antidepressant_Use_Ratio_on_Energy_Intake =
GRAPH(Antidepressant_Use_Ratio)
(1.00, 1.00), (1.12, 1.00), (1.25, 1.01), (1.38, 1.01), (1.50, 1.02), (1.62, 1.03), (1.75, 1.04),
(1.88, 1.04), (2.00, 1.04)
UNITS: Unitless

Target_Effect_of_Income_ratio_on_ease_of_purchasing_healthy_foods =
GRAPH(Percentage_of_Annual_Income_Allocated_for_Food_Ratio)
(1.00, 1.00), (1.00, 1.00), (1.00, 1.00), (1.01, 1.00), (1.01, 1.00), (1.01, 1.01), (1.02, 1.01),
(1.02, 1.02), (1.02, 1.03), (1.02, 1.04), (1.02, 1.04), (1.03, 1.05), (1.03, 1.05), (1.03, 1.06),
(1.04, 1.06), (1.04, 1.06), (1.04, 1.07), (1.04, 1.07), (1.04, 1.07), (1.05, 1.07), (1.05, 1.07)
UNITS: Unitless

Target_FX_of_Emotional_Eating_on_Energy_Intake =
GRAPH(Emotional_Eating_Ratio)
(1.00, 1.00), (1.20, 1.00), (1.40, 1.00), (1.60, 1.01), (1.80, 1.02), (2.00, 1.04), (2.20, 1.06),
(2.40, 1.08), (2.60, 1.09), (2.80, 1.10), (3.00, 1.10)
UNITS: Unitless

Time_to_Adjust_Normal_Antidepressant_Use = 365/2
UNITS: days (day)

Time_to_Change_Average_Annual_Cost = 365
UNITS: days (day)

Time_to_Change_Potential_Annual_Salary = 365
UNITS: days (day)

Time_to_Update_Daily_Rec_PA = 1
UNITS: days (day)

Time_to_Update_Daily_Util_PA = 1
UNITS: days (day)

Time_to_Update_Normal_Emot_Eating_Level = 365/2
UNITS: days (day)

TIme_to_Update_Normal_Percentage = 365
UNITS: days (day)

Time_to_Update_Normal_Stress_Level = 365/2
UNITS: days (day)

Time_to_Update__Leisure_Activity = 1
UNITS: days (day)