2016

A HAPA Inspired, Agent-Based Model and Simulation of Activity in an Online Community

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A Thesis
Submitted to the Faculty of Graduate Studies
Through the School of Computer Science
In Partial Fulfillment of the Requirements for
The Degree of Master of Science at the
University of Windsor

Windsor, Ontario, Canada

A HAPA Inspired, Agent-Based Model of a Spinal Cord Injury Community

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16 December 2016

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ABSTRACT

This thesis is an examination of a Health Action Process Approach (HAPA) developed originally by R. Schwarzer for use in understanding and effecting health behaviour adoption. Although HAPA provides an integral aspect of formulating health treatment strategies by human practitioners for human patients, at the present time no simulation models suited to computer implementation and usage exist for the study of and support for health behaviour adoption within a HAPA framework.

This thesis examines the relevant research with respect to HAPA and the components necessary to build a simulation model and platform for an online, self-managing SCI community. We design an architecture for the platform that satisfies the primary requirements suggested by HAPA and SCI patients, particularly directed at gathering relevant data consisting of health indicators. Also, we develop several algorithms used for analysis of HAPA related health states and transitions between states. Since this research did not involve any human subjects, the intention was to simulate certain critical behaviours and changes using an agent based modeling approach. Inasmuch as agents can provide only approximations to real human behaviour, they are still useful and informative.

As part of our results, we show that an automated HAPA classification can reduce the risk of agents dropping a health behaviour or program due to misclassification. Further, findings revealed that 6% of the agents are in danger of dropping the adoption of an individual health behaviour within two weeks and that 14% of the agents are at risk of dropping out of the community without continual HAPA reclassification.

DEDICATION

I dedicate this thesis to my mother who died of complications resulting from a chronic disease, in hopes that this work will assist with the design of future self-management programs for chronic illness.

ACKNOWLEDGEMENTS

I would like to acknowledge all the support from my friends and family whose encouragement was paramount at times, the direction and assistance provided by my committee and graduate staff, and the inspiration from the SCI community who demonstrated a genuine meaning of community. I would like to thank the Craig H. Neilsen Foundation for funding the Parkwood Hospital development of the URinCharge online community, which provided most of the motivation for this thesis. I thank the Parkwood staff for allowing me to participate in the URinCharge project, and my supervisor for his guidance and patience that enabled this thesis. Finally, I acknowledge funding received from the Craig H. Neilsen Foundation in partial support of this thesis research.

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CHAPTER 1
Introduction

1.1 Motivation

Imagine you are going to visit a friend, along the way you are involved in some kind of accident and you wake up in an ambulance. After awakening from emergency surgery, you find out that you have sustained a spinal cord injury; it is immediately clear that you have lost a significant degree of your ability to move your legs, your body and your arms. You are now one of the 4,300 Canadians who sustained a spinal cord injury (SCI) this year [1]. Today 86,000 people are living with a Spinal Cord Injury in Canada, and this figure is projected to be 121,000 by 2030 [1]. Many of the symptoms associated with SCI are treatable; however, the conditions related to SCI, including restricted mobility and loss of control of bladder and bowels, among others, are not curable (at least, not at this time). As a result, SCI is considered to be a chronic illness along with hypertension, asthma, chronic obstructive pulmonary disease (COPD), diabetes, and arthritis, to name a few conditions.

Chronic Disease is a human health condition or disease that is persistent or otherwise long-lasting in its effects. As a person with SCI, your life has changed; you will be involved with self-management programs and self-assessing your health for the rest of your life. In addition to the mobility issues you will now visit your physician 2.7 more often, be hospitalized 2.3 more often, and live 15 – 30 years less than you would have before the accident [1]. Patients with chronic illness are plagued with secondary issues associated with their disease, and 58% of family physician visits were related to secondary complications for SCI patients [2] [3]. To mitigate these facts, you will need to manage behaviours you took for granted in the past.

Hygiene, fluid intake, physical activity, bladder management, and monitoring yourself for secondary complications have just become your priorities to improve the quality of your life.

Historically, the management of chronic disease has been a doctor or nurse centred approach involving an application of treatment to the patient by trained health practitioners. Today, self-management has been found to be critically important for improving chronic disease outcomes by engaging patient clients directly, as participants and stakeholders, through education, self-monitoring, goal setting, and peer support to promote healthy behaviours [3] [4].

Self-management interventions currently use Patient Reported Outcomes (PROs) to monitor a person's progress in a program and the program overall success. PROs provide a patient's feedback on their feelings or what and how they can do as they deal with their chronic diseases or conditions [5] [6]. PROs typically cover three areas, or domains: physical, mental, and social health. The following are simple examples of PROs:

- I always drink 6-8 cups of water a day.
- I rate my physical health as poor.
- I feel like something awful might happen.

Typically, such self-assessments utilize non-standardized measures such as Likert scales. Although proven effective in health practice, PROS are criticized because they are subject to a range of biases, such as poor memory or inability to summarize past experiences accurately [7] [8]. Smoking patients tend to underestimate the benefits and overestimate the deficiencies [9], and participants sometimes inflate estimates of control [10].

Researchers and clinicians are currently developing and modifying self-management programs for the SCI community. URinCharge is an example of a SCI self-management program at the Parkwood Hospital in London, Ontario, Canada [11]. The URinCharge self-management platform refers to the Health Action Process Approach (HAPA) framework, due to Ralf Schwarzer [12], as a basis for development.

This thesis describes and documents an investigation into the feasibility and benefits of automating HAPA classification within an online self-management system. If we can augment PROs with data from the online community not subject to human biases, we could, in principle, improve HAPA categorization and ultimately improve the online self-management experience.

1.2 The Problem Context

Chronic illness is costing Canada over $80 billion each year. The current models in health care are not suitable for modeling individual patients within a self-management program [13] [14]. The analytical tools used in health are primarily diagrammatic logic models and epidemiological forecasting models. These models are not well suited to capture the dynamic complexity of chronic diseases [15] [16] [17] [18] [19]. Brailsford categorized health models as:

- Models of the human body frequently called "disease models."
- Models for tactical purposes at the healthcare unit level.
- Models for strategic purposes comprising system-wide models.

These models are not intended for, nor are they capable of, modeling individual actions.

The SCI online community currently under development [11] will not be released for purposes of gathering patient data until 2017; hence, it will not be capable of supplying data for this investigation into the feasibility and benefits of automating HAPA classification. There are no suitable simulation models for individual intervention planning, new tool impact assessment, and prediction of a community's general health status based on the HAPA framework [20]. Currently, clinicians are designing online self-management programs basing many design decisions on unproven assumptions rather than results from a model. Thus, there is no real data available for this study, or models to generate the data.

1.3 The Proposed Approach

To overcome the lack of real human data and suitable HAPA simulation models, we decided to develop a model to simulate activity within the SCI online community using an Agent-Based Model (ABM). We used the model to understand the benefits of automated HAPA classification by studying when agents abandoned health behavior adoption or dropped out altogether.

1.4 Contribution

In this thesis, we have done the following:

- We outline a HAPA inspired online community, suitable for any treatment of any online community (Section 2.4).
- We design the components of the Agent-Based Model (ABM) (Section 4.3).
- We outline the online HAPA classifier to be used in the real SCI online community (Section 4.5).
- We verify our model actions against the logic programmed into the agents since there is no data set suitable for validation (Section 5.1).
- We analyze the simulation results to understand the benefits of automated HAPA classification (Section 5.3).

1.5 Organization of Document

The remainder of this thesis is organized as follows. Chapter 2 introduces the reader to the relevant background information on the HAPA framework and various health and behavioural factors necessary to design and build a HAPA inspired ABM of an online community. Chapter 3 contains the thesis problem, hypothesis, objectives, and methodology. Chapter 4 describes my solution and implementation, including the reasons behind choices we made in our design. Chapter 5 includes the results of the simulations and discussion of the model validation. Chapter 6 concludes the thesis and also presents some areas for future research.

CHAPTER 2
HAPA and Online Communities

In this chapter, we introduce the relevant material pertaining to this thesis. We begin by briefly looking at Agent-based modeling (ABM). Then we examine health behaviour adoption to gain an understanding the interaction between the agent and the SCI online community. Next, we look at the factors that will drive the agent's actions and decisions. We conclude this chapter with an examination of the SCI online community in development.

2.1 Agent-Based Models

The purpose of the thesis is to simulate the use of an SCI online community by real people as they attempt to improve their quality of life by adopting and maintaining prescribed health behaviours. In this section we will briefly review computer simulation and ABM, to ensure that it is suitable for modeling the online community. Finally, we will briefly discuss the use of fuzzy logic as a means to have the agent actions appear less binary.

Computer simulation is the process of running a computer model to reproduce the behaviour of a system or network. In this case, the simulation would repeatedly be running a model of the online community while using its output as the input to the subsequent run. Computer models are used in a variety of disciplines, from astrophysics to weather forecasting, using a variety of tools and platforms. Agent-based modeling (ABM) is a preferred method when modeling complex reactive systems.

An ABM is a modelling paradigm, which utilizes agents to simulate the actors within the system of study. For instances in modelling the SCI online community an agent would represent an SCI client; while, in modelling geese flight an agent would represent a single goose. The term “agent” is widely used in modelling, without a standard definition [21]. An agent is more often defined in literature by it attributes rather than by a single definition. This is most likely because the agents within models differ between fields of studies. For the purpose of this thesis, we will use the following to define an agent. An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through an actuator [22]. An agent needs to possess the following general characteristics to accomplish its task: independence, learning, cooperation, reasoning, and intelligence [22] [23] [24]. An intelligent agent performs, reactively and or pro-actively, interactive tasks tailored to a user’s needs without humans or other agents telling it what to do [23]. Please remember that an agent is still only a software program that operates within a given environment performing only the actions for which it is programmed. Agents are used in modelling to gain insight into the system’s behaviour and outcomes.

As stated above ABM is a preferred method when modeling complex reactive systems and has been used in health for modelling the complex dynamics associated with obesity [25], and as a basis for a decision support system managing patient falls in a hospital setting [26]. ABMs have also been used to model behaviours in child seat use [27], and to model other health frameworks [24]. Finally, an ABM has also been used to model ancient societies [28]. Modelling behaviours require ABM techniques because it requires independent agents to model complex individual and social interactions [29] [30].

To simulate the online SCI community we need to mimic human interactions with an online system. Although not as complex as modeling an ancient civilization, we will need to simulate the agent's actions driven by the factors discussed in Section 2.3. Given that, this model must simulate people’s complex actions within the SCI online community it would appear that an ABM is an acceptable approach for modelling the SCI online community.

There are varieties of ABM platforms ranging from desktop models to high-performance computing. The desktop platforms range from excel spreadsheets to open source and licensed software. MASON, Netlogo, Repast, StarLogo, ZEUS are just a few of the popular software packages encountered during this research. We started the modelling efforts using Repast because of the support available within our lab and online. Repast was quick and easy to install and provided the necessary infrastructure to construct an ABM. ABMs require more than a platform to be successful. According to Macal and North an ABM, requires the modeler to consider the following points. 1) Identify the agents and the factors that drive the agent behaviour. 2) Identify the relationships and in the agent interactions within the model. 3) Select or design and develop suitable ABM platform. 4) Get the agent-related data. 5) Validate the agent behaviour. Finally, 6) run the model and analyze the output from an individual and system basis [21]. To satisfy Macal and North’s first two requirements, we will examine health behaviours to understand the interactions between the agent and online system in Section 2.2 and the factors that will drive the agent behaviour in Section 2.3. The remainder of Macal and North’s requirements are discussed in Chapters 4 and 5.

2.1.1 Fuzzy logic

In this section, we discuss fuzzy logic as a means to make the agents appear more realistic and less deterministic. The questions that we answer daily, such as “Do you feel healthy enough to proceed?”, are trivial to us; but, an agent must use fuzzy logic to appear more realistic and less binary. Fuzzy Logic allows classification engines and ABMs to handle unclear (fuzzy) values. The core of both classical and fuzzy logic is the idea of a set. In classical set theory, an element belongs or does not belong to a set. The fuzzy set theory permits the gradation of the membership of the element in a set [31]. The central term in this fuzzy logic is the "fuzzy variable." In the logic domain, the fuzzy variable is one that can deal with values from zero to one, in contrast to the Boolean variables that can assume only the values 0 and 1 [32]. An application of fuzzy logic can be seen in Figure 2.1. The vertical line in the image represents a particular temperature that the three arrows (truth values) gauge. Since the red arrow points to zero, this temperature may be interpreted as "not hot." The orange arrow (pointing at 0.2) may describe it as "slightly warm" and the blue arrow (pointing at 0.8) "fairly cold." You can also state that the value belongs to the cold set with degree .8 and the warm set with a degree of .2.

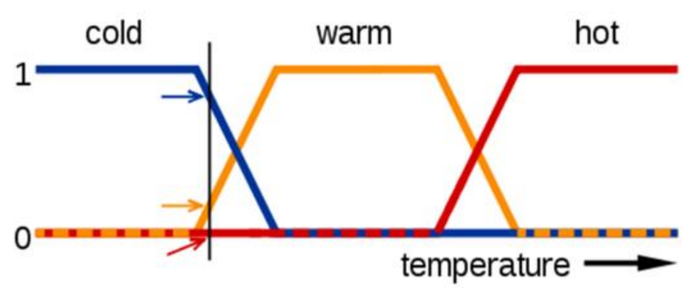

Figure 2.1: Fuzzy Logic [33]

Fuzzy logic is well-known for its strength in managing classification problems where boundaries between classes are ambiguous [34]. One of the hallmarks of fuzzy logic is that it allows nonlinear input and output relationships to be expressed by a set of qualitative “if-then” rules [35].

Above, we briefly reviewed computer simulation and discussed fuzzy logic as a method to deal with unclear or fuzzy decisions. In the next section, we will discuss the factors that will drive the drive the agent actions.

2.2 Health Behaviour and HAPA

The Health Action Process Approach (HAPA) is a psychological theory of health behaviour change, developed by Ralf Schwarzer [36], which has been applied to individuals or communities. In this section, we will briefly examine HAPA role in treating chronic illness, its current measures, its self-efficacy, and its health adoption predictive capabilities, in order to gain an understanding of how a community will interact with individuals. For the purposes of this thesis, this will translate into a model of the relationship between an online community and software agents.

HAPA is an open-ended (or multi-phased) "… framework of various motivational and volitional constructs …" that are assumed in order to explain and predict individual changes in health behaviours [10] [37]. Individuals are categorized into a framework for each behaviour they are trying to adopt.

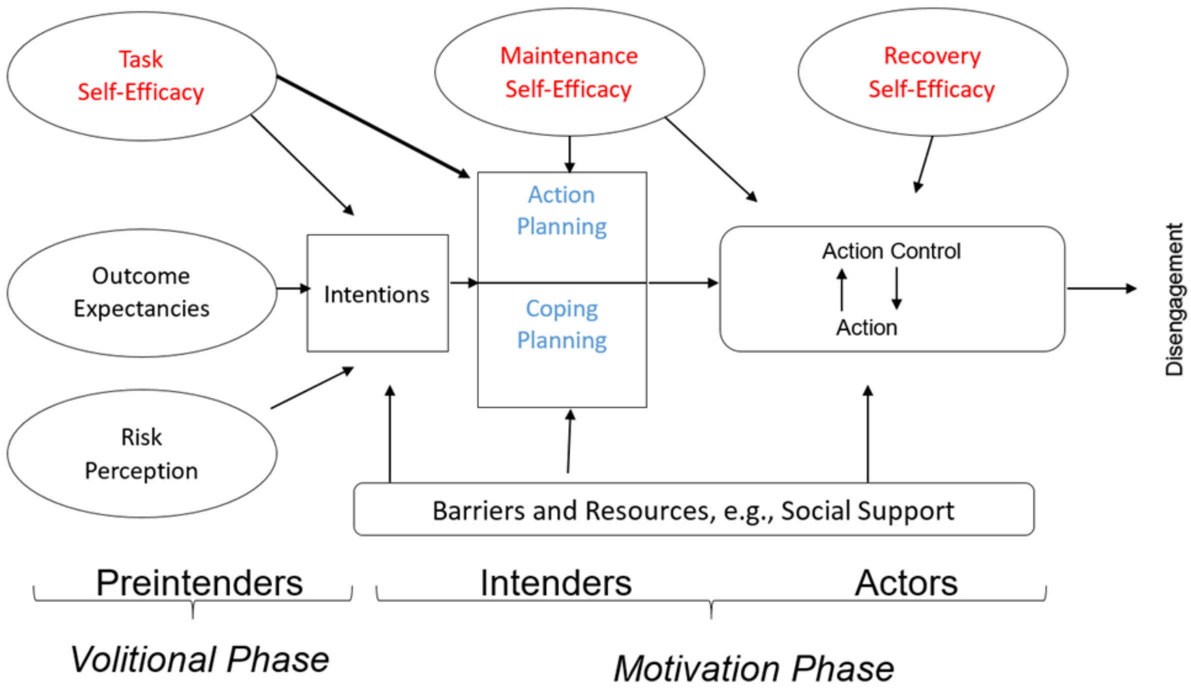

Figure 2.2: HAPA Diagram (adapted from Ralf Schwarzer [36]*)*

Figure 2.2 shows the phases and classifications inherent within HAPA. A person who is in the volitional phase is characterized as a Preintender and is trying to move from wishing they would adopt the behaviour to where they will start to adopt the behaviour. In this phase, Preintenders review their priorities, weigh the pros and cons of actions, and eventually decide to adopt or not adopt a health behaviour (e.g. dieting, using condoms, or giving up smoking). The Motivational phase is divided into the Intender and Actor stages. Intenders have decided to adopt the behaviour, but, have yet to start. They are in the process of planning how to overcome their remaining barriers. Finally, those who have begun to adopt their behaviours are classified as Actors.

The HAPA framework is just one of many frameworks that are used to understand behaviour change. For instance, the HAPA framework is a hybrid model that can be substituted for the Transtheoretical and Health Belief Models [38], both of which are widely cited in the literature for the understanding of health behaviour adoption.

2.2.1 HAPA role in chronic disease treatment

HAPA as stated above, is just a framework used to explain and predict individual changes in health behaviours. HAPA has been used as the basis for the development of several self-management programs and tools used to promote such behaviours as: seat belt use; breast examination; and, physical activity for people with Multiple Sclerosis [10]. Historically, treatment has been a doctor or nurse centred approach involving the application of a treatment regimen to a patient; however, self-management has been found to be critical for improving chronic disease outcomes by engaging clients through education, self-monitoring, goal setting, and peer support to promote healthy behaviours [3] [4]. Programs and tools based on HAPA first categorize a client into one of the HAPA stages and then tailor the delivery of materials intended to meet their needs. Examples of a tailored delivery could be providing discounted gym memberships to an Actor who is trying to lose weight, a list of gyms with daycare for an Intender with children, and, finally, material reviewing the benefits and deficiencies of weight loss to Preintenders.

2.2.2 Self-Efficacy

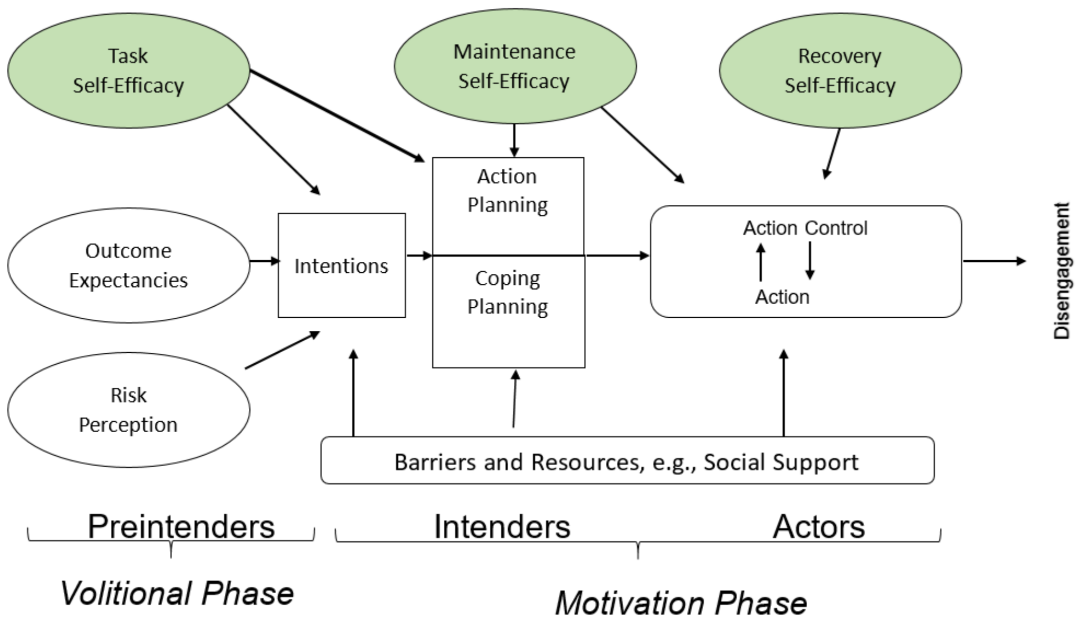

Figure 2.3: Self-Efficacy within HAPA (adapted from Ralf Schwarzer [10])

Self-Efficacy represents one-third of the HAPA diagram as highlighted in Figure 2.3. Self-Efficacy must be accounted for in any HAPA simulation model. Self-Efficacy is an individual's perception of what they can accomplish given their current circumstances and it influences a person at each HAPA stage, since people are more likely to engage in activities for which they have high Self-Efficacy and less likely to engage in those they do not [39]. We equate Self-Efficacy to "I can. Therefore, I will". Self-Efficacy must not be confused with Self-esteem, which is a feeling of self-worth.

In the HAPA diagram context, Schwarzer asserts that task, maintenance, and recovery Self-Efficacies are required to adopt fully and maintain a health behaviour. Task Self-Efficacy is seen as predisposing factors in the goal-setting (motivational) phase, whereas planning, action control, maintenance and recovery Self-Efficacy are regarded as being influential in the subsequent goal-pursuit (volitional) phase.

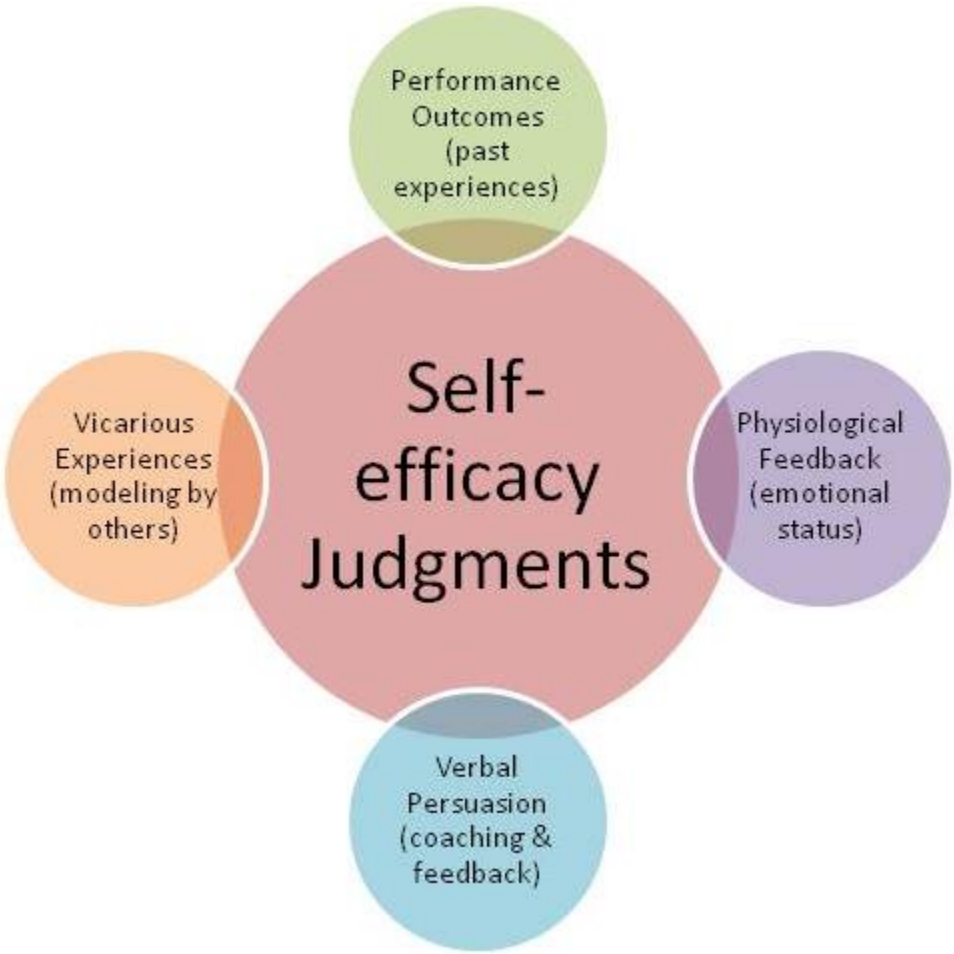

Figure 2.4: Sources of Self-Efficacy (adapted from Bandura [40])

Figure 2.4 is just one of many similar images showing sources of Self-Efficacy [41], particularly a perspective created by Bandura showing four sources of information that individuals use to judge their efficacy [40]. Self-Efficacy is primarily a function of your experiences, peers experiences, and social persuasion [8]. Studies have shown that mastering similar tasks or behaviours is the most influential source of efficacy information because they provide the most authentic evidence of whether one can muster whatever it takes to succeed [12]. Mastery can be characterized as: “You’ve done it before. You can do it again.” Lacking personal experience, we next use our vicarious experience to judge if we can muster what it takes to succeed, which can be characterized as: “My friends have done it so I can do it too.” Verbal persuasion can take the form of advertisements, pamphlets, and social influences, and its effectiveness depends on the credibility of the persuader. Finally, physiological feedback refers to your comfort level with the task; this feedback is usually the least influential of the four factors.

2.2.3 Health Behaviour adoption

In this section, we explore the question: Can health behaviour adoption be predicted by looking first at health behaviour adoption, as a baseline, and then investigating if others have been able to predict health behaviour changes towards adoption?

When you first look at the HAPA diagram, it suggests that you might be able to use a simple equation to calculate when a person would move from a Preintender to an Intender. However; behaviour change is not necessarily linear and may be best represented as a series of interactions that contribute to a person’s knowledge, attitude, efficacy or intention which could trigger a behaviour change [6]. Each interaction contributes to an individual’s knowledge; this varies between individuals. My favourite metaphor of knowledge gain is from an unknown author who represented knowledge gain as a sack of balls covered in a sticky substance where the balls are the artifacts the sticky substance is knowledge. As people extract and replace the balls the residue on their hand represents the retained knowledge, they gained. As an individual or agent interacts with the online community, their interactions affect their knowledge. Since the online community contains vetted resources and is monitored, we can assume that most interaction will result in a positive gain in knowledge, attitude, efficacy or intention. Knowledge has proven to become less effective over time [8], and that is why the HAPA goal is to provide the material at the right moment.

We found that the HAPA framework has been used successfully to obtain health behaviour adoption in physical activity, exercise adherence, breast self-examination, seat belt use, dietary behaviours, and Dental Hygiene [13] [42] [43]. PROs and other evidence measures have been used in predicting dietary change [9], participation in a breast screening intervention [29], and determining HAPA Intenders and non-intenders [3].

HAPA variables have been used to establish HAPA stages, participation, and outcome of behaviour change interventions. The challenge is to identify a set of variables and outputs, which can be for categorization in the simulation model. The online community can utilize PROs for HAPA categorization; however, looking ahead in the thesis, the simulation model to be established in Chapter 4 and discussed in part in the following section, requires an automated HAPA categorization, since PROs cannot be reasonably administered during the computer-based simulation. The model as discussed in Chapter 4 must represent pertinent PROs such as an average health score and other attributes, since as mentioned in Section 1.3, we lack of real human data suitable for the simulation. That is not say that PROs are not available on a variety of health topics, they are just not suited for our modelling.

2.3 Factors

In this section, we will examine the factors, which drive agent interactions within the simulation model. The online community, by its nature, currently limits the actions that an agent can perform to provide a safe moderated online experience. The agents can only research topics of interest, interact with other agents via forums to develop relationships, utilize toolkits to track health variables such as water consumption, or ask for assistance; but, how they use the online community still needs to be established to program the agents. Specifically, we need to answer these questions:

1) What causes someone to stop or drop the program?

2) What will they do in the online community?

3) What drives their online selections?

4) How long are they online?

2.3.1 Adherence

Adherence and compliance are terms used to describe the degree to which a patient correctly follows medical advice. In a perfect world, everyone who started a self-management intervention program would continue with the program. We know that this is not true in the real world. Therefore, in this section we will examine some reasons, or identifiers, for adherence that we can reasonably emulate in the ABM.

Studies have shown that patients continue, on average to take about 50% of prescribed medication [44], and 25%–40% patients are not adherent [39]. In a study on compliance, it was noted that there is no reliable way to measure compliance and that the term was not used consistently between studies [45] which, conversely, explains why there is no ultimate list of non-adherence reasons. Munce *et al*, in a study to understand perceived facilitators and barriers to self-management to prevent secondary complications in SCI community, found physical limitations, funding, accessibility, mood , caregiver burnout, and control over care to be barriers that need to be overcome to achieve adherence [46].

We found the reasons vary between studies depending on the field of study; but, a typical list of reason were conflicting information, costs, religious beliefs, lack of time, lack of resources, the time span of treatment, and ineffective treatment [47]. The latter two reasons can be represented in our model. In addition to the reasons which can be modeled, we must account for people randomly dropping out of a behavior adoption or the complete program. The model must account for agents dropping out when they see no progress, when they are given incorrect material, and even randomly to account for the other reasons, which cannot be modelled individually.

2.3.2 SCI Community Current Internet Use

In this section, we briefly examine SCI population use of the Internet to understand what actions the agents must be able to perform.

The SCI community currently uses the internet to improve their general quality of life and will most likely use the future online community to improve their health-related quality of life [47] [48]. The benefits and uses of the internet by the SCI community has been well studied, but from results rather than an action perspective which is needed to develop a model. To understand the actions that were used by the SCI community to achieve their results, we need to examine discussion forums. Pendry describes these actions as seek information, share information, form relationships and discussions with likeminded people [49]. Pendry's actions are reflected in Miller's article, which studied the internet use in individuals with spinal cord injury [50].

The SCI population uses the internet for a variety of reasons, but the interactions boil down to seek information, share information, form relationships and discuss with like-minded people especially in an online forum.

2.3.3 Personality Effects and Learning Styles

In this section, we examine how personality and learning styles could drive an agent behaviour in the online community. Traditionally, extroverts were considered more outgoing, and introverts were seen as shy. The intranet and the anonymity it provides has changed how everyone interacts. It has been found that extroverts prefer communication media that enable direct and immediate contact with others, and they join more groups [51], while introverts prefer to use computer-mediated communication means for their communication and research to help reduce anxiety [51] [52]. These studies agree with the traditional view; however, other studies have found that low risk and familiar Internet service usage are not affected by personality traits [52], and self-esteem was found to be an important personality characteristic that significantly identifies media choice [53]. The internet appears to be associated with any of a range of trait and cognitive personality variables [54], and results differ from study to study depending on the field. Therefore, we will use the definition of introvert and extrovert loosely allowing an agent to be between being a total introvert or extrovert.

Personality traits could not be correlated to time spent in online communities or amount of data shared [51]. Miller found that the SCI community spent about 29 hours a week online of which 12 hours is social and disability related [50], which is just slightly above the social worldwide average 11.9 hours a week excluding teens [55].

Learning styles are not as controversial as personality traits with respect to computer use, but they still play a part in how we approach the task at hand. Your learning style is simply your preferred method of learning. Ford and Moss could not link cognitive learning styles an internet search study [56]. They discussed the importance of Self-Efficacy in information retrieval and touch on the term *globetrotting*. Merriam et.al discuss global and analytical processing styles in adult learning, which describe how one receives and processes information [57]. A global learner processes multiple ideas and experiences in a global fashion, while an analytic learner processes information in a step-by-step objective manner. In the model, the analytic learner will focus on their most important while the global learner will attempt to address all at once.

2.4 HAPA Inspired Online Community

In this the final section of the design chapter, we need to outline the actual online community being developed. The online community will become a main interaction point for the SCI community, and the only interaction point for the agents. Therefore it is imperative that the Online community is reflected in the model.

The ultimate goal of the online community is to help a person adopt the necessary health behaviours by providing a safe environment where one can gain the will and the way to improve their individual circumstances. The online community will provide a personalized experienced based on HAPA level, pertinent physical characteristics and have a social environment to promote friendships and encourage ongoing use of the community because chronic disease management is never ending.

There are a variety of tools which can be configured to achieve a community. The online community as described by the SCI community in workshops consists of the following:

- themed HAPA filtered repositories (libraries),
- forums,
- discussions boards,
- personal blogging tool with tagging and voting capabilities,
- a variety of applications or trackers designed to address individual health concerns,
- HAPA categorization engine,
- and, most importantly, a human advocate to address concerns which cannot be resolved by an online community.

The SCI community has eight health behaviours of interest and approximately fourteen areas of interest as taken from current SCI discussion boards.

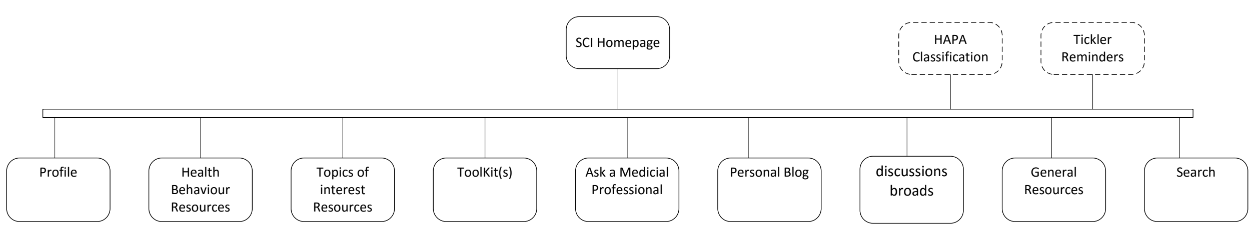

Figure 2.5: SCI Site Overview

The essential components as seen above in Figure 2.5 exist in many websites today for the SCI community except the HAPA classification and filtering. The HAPA Classification and Tickler processes are shown as dotted boxes since they are background processes. The site enforces a strict registration, assessment and initial HAPA classification process flow before granting access to any resources to achieve the full benefits of personalization. The initial account setup is currently a vetted process ensuring that all users have a legitimate reason for belonging to the community. Figure 2.6 shows the login process forcing clients to register and take an assessment before being allowed to navigate the SCI online community. The personalization is required for achieving a HAPA inspired online community since it ensures that the clients receive the appropriate material given their current HAPA stage.

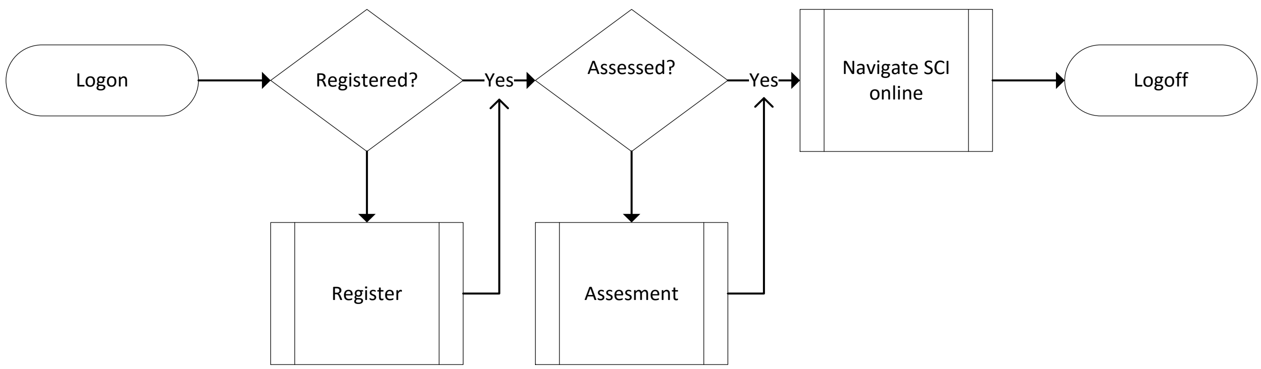

Figure 2.6: SCI Logon Flow

The toolkit(s) are a combination of resources, goal setters, trackers, and community and friend comparison applications. The goal is to foster a supportive atmosphere to encourage program adherence through peer pressure and competition. During the workshop, it was mentioned by several of the participants that they adhered to their goals to avoid disappointing their peers. Toolkits also have the ability to be programmed with logic to recognize when a person has progressed to the next HAPA level. An example of toolkit classification could be that once a person maintains a healthy water intake for a month, they are automatically classified as an actor.

2.5 Summary

In this chapter, we discussed the key elements of the thesis required to build a HAPA inspired ABM. We introduced health behaviour by discussing HAPA, Self-Efficacy, and health behaviour adoption which are key to the SCI online community. Then, we discuss computer simulation and the factors that will drive the model and agent behaviour. Finally, we introduce the SCI online community. In the next Chapter 3, we present our thesis problem, our thesis hypothesis, our research objectives, and our methodology.

CHAPTER 3
Thesis Hypothesis and Methodology

In this chapter, we will discuss the thesis problem, our hypothesis, objectives, and research methodology.

3.1 Thesis Problem

As we have presented in Chapter 2, HAPA is a framework, used for many self-management programs, which has proven successful in understanding the adoption of health behaviours [10] [36] [58] [59].

At the time of this writing, HAPA categorization within self-management programs appears to be based primarily on Patient Reported Outcomes (PROs). Although proven effective, PROS are criticized because they are subject to a range of biases, such as poor memory or inability to summarize past experiences accurately [7] [8]. Smoking patients tend to underestimate the pros and overestimate the cons [9], Participants sometimes inflate estimates of control [10]. We could not find any mention of automated HAPA classification in the research literature reviewed.

As mentioned in Chapter 1, our work began with a funded research project, called URinCharge [11], to design and implement a web-based framework for Spinal Cord Injury patients and the online community they are part of, including other patients and health professionals. The SCI online self-management program currently uses PROs for HAPA classification. HAPA classification is used to personalize the client online experience. If the HAPA classification is incorrect, so will be the treatment. HAPA categorization of individuals will occur at the beginning, at registration into the system, and throughout the program on a scheduled basis; we note that scheduling, if not done correctly, can increase dissatisfaction between classification periods.

At the time of working on this research and thesis, the SCI online community URinCharge was still in active construction and validation; hence, we were not able to gather sufficient data for an investigation into the feasibility and benefits of automating HAPA classification. However, there are no simulation models for individual intervention planning, new tool impact assessment, and prediction of a community's general health status based on the HAPA framework [20]. Thus, we determined that to investigate automating HAPA classification an Agent-Based model (ABM) of an SCI online community could be developed to study the feasibility and benefits of automating HAPA classification. This is the essential problem addressed by this thesis research.

3.2 Thesis Hypothesis

To address the problem defined in the previous section, our hypothesis is:

> *As people (or agents) seek to satisfy their individual needs in an online community (or simulated environment), their activities can be classified by HAPA Stage.*

From a computer science perspective, this statement may be stated in the form:

> *An Agent-Based model (ABM) is appropriate to study simulated SCI patient behaviour relating to needs and activities, and to provide automated classification according to HAPA stages.*

Inasmuch as the hypothesis statement is somewhat abstract and vague, in order to describe in simple terms the nature of complex software systems, we provide a more detailed list of specific objectives in the next section.

3.3 Objectives

In order to validate our hypothesis, we considered the following objectives as necessary elements of our research work:

- Design the software framework and elements required to model and simulate activity within a HAPA inspired online community.
- Build a HAPA inspired ABM of the SCI online community.
- Quantify and evaluate the benefits, and potential deficiencies, of automated HAPA classification.

3.4 Methodology

The URinCharge project [11], which has stimulated many aspects of this thesis research, is based on a Participatory Action Research (PAR) methodological approach. This is reasonable due to the kind of innovative health research presented by such self-management approaches and platforms, where all participants for whom the platform is intended must be involved in order to ensure that their various interests are properly met. Although this thesis research work is independent of the PAR paradigm, we have had significant opportunities to interact with a multi-disciplinary team of experts and SCI clients to understand better, and more completely, the nature of the future HAPA online community.

Since PAR must be excluded from consideration, we adopted a system design based approach to our methodology. Thus, my approach consisted of the following steps:

1. Assist with the design and development of a HAPA Online Community through a thorough investigation of needs, stated in the forms of requirements and specifications.

   A solid understanding of the online community is required before it can be modeled and simulated.

2. Literature review.

   Review the pertinent literature on HAPA to serve as a basis for the Agent-Based model, and for modeling agent actions.

3. Agent-Based Model Development

   a) Design the ABM

      A stochastic Agent-Based Model of the SCI online community must be designed, based on recent studies of SCI and HAPA classification models.

   b) Build the Agent-Based Model

      The SCI ABM programs has been developed in C# to accommodate moving the categorization engine eventually to the proposed SCI online community, URinCharge.

   c) Validate the model output.

The model output has to be subjected to logical consistency evaluation as a replacement for formal validation; no HAPA or similar community exists, at this time, that is capable of supplying real data for formal comparison and analysis.

d) Investigate thesis question.

Once the model is verified for logical consistency, we will investigate and quantify, wherever possible and reasonable, the benefits of automated HAPA Classification.

3.5 Summary

In this Chapter 3 we have presented the problem underlying this thesis research, both from the perspective of designing and building a intervention and support tool for self-management of health among persons with spinal cord injuries, and also from the viewpoint of designing and building appropriate, complex software systems that support the health driven objectives. One vital aspect that defines the problem is incorporating the HAPA model into the software design. This led to our hypothesis that an Agent-Based model (ABM) is appropriate to study the SCI patient behaviour relating to needs and activities, and provide automated classification according to HAPA stages; these stages are used as indicators of adherence, or commitment, to maintaining positive health strategies. We then proceeded to state several specific objectives needed to verify our model and simulation results and provided a detailed methodology for carrying out the research program.

In the next Chapter 4, we present and discuss the ABM developed for this research.

CHAPTER 4

ABM Design

In this chapter, we will present and discuss how to translate the HAPA framework from a health practitioner perspective into a suitable software architecture and the computable software components necessary to build the model. The primary goal of the Agent-Based model is to: simulate individual interactions with the online community using an Agent-Based modeling approach; provide input to a HAPA categorization engine; and, provide clinicians with a tool to test assumptions on filtering and classification strategies.

4.1 HAPA Online Community Representation

To model the online community, we need to represent the community in a digital form for the agents. This will establish the environment in which agents interact. The online community consists of themed HAPA filtered repositories (libraries), forums, discussions boards, a personal blogging tool, and a forum to ask a health professional or advocate to address concerns which cannot be resolved by an online community. In this section, we describe how to represent the online community to the agents.

We can all envision the individual components of the online community, but to the system, everything is just a resource referenced by an address or globally unique identifier (GUID). We view libraries as a series of documents, or a forum as a series of messages, often focusing on the title or another attribute. The actual system is presenting us a series of GUID links sorted on an attribute. This GUID link between us and the document allows us to represent the online community as a series of arrays with ascending GUIDs rather than focusing on the titles.

HAPA library 1 GUIDs	1	2	3	4	i
HAPA library 2 GUIDs	i+1	i+2	i+3	i+4	.....j
:	:	:	:	:	:
Forums	k+1	k+2	k+3		...n

Table 4.1: Community Representation as GUIDs

In our online community as seen in Table 4.1, we have eight HAPA arrays, one for each health behaviour that the SCI community needs to address. Initially, the HAPA arrays would contain the GUIDs 1 – 16000 assuming that there are 4 HAPA levels (including the non-intender) and each repository having 500 resources available. Any non-static additions after the initialization such as forum entries would be assigned the next GUID as seen in the table above as GUIDs k+1 …k+3.

4.2 Computational HAPA Model

The HAPA model provides an excellent flow chart for understanding what influences a person while adopting a health behaviour; however, the HAPA model alone is not sufficient to create an agent within an Agent-Based model (ABM). To be able to configure an agent within a HAPA inspired ABM, we converted Schwarzer's model to a state like diagram shown in Figure 4.1, where each HAPA level is a state resulting from an agent interaction.

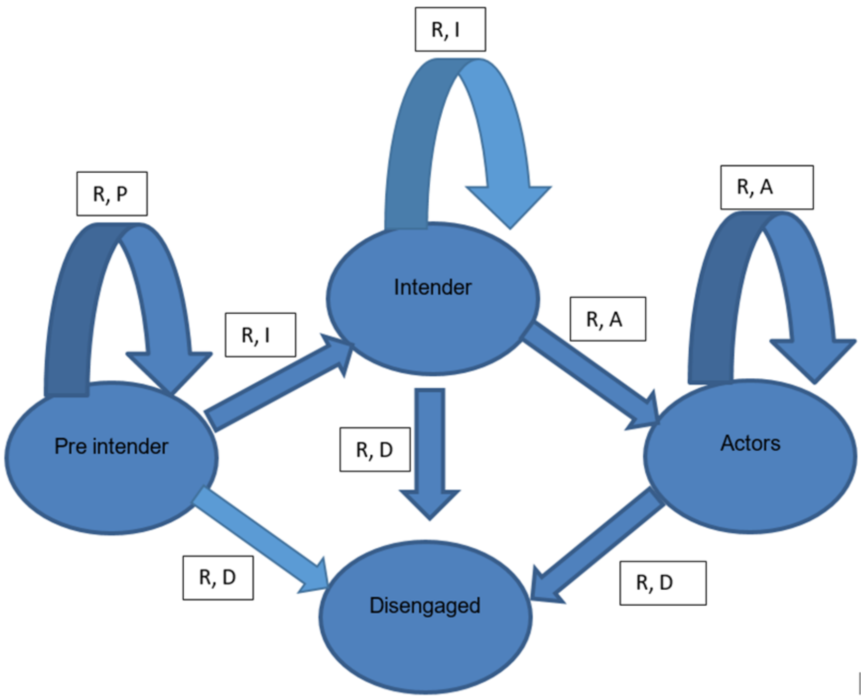

Figure 4.1: HAPA State Diagram (adapted from Schwartwarz's HAPA Model [21])

In the diagram, each arrow represents an interaction with the online community. The R in the arrow represents the result from the agent interaction followed by the resulting HAPA stage. The results from the interaction can be a resource HAPA library resource, a forum reply, an answer from the nurse, a friendship formed, or nothing because they just posted a question followed. Once the agent has collected the necessary resources and achieved a sufficient Self-Efficacy level, they can ascend to the next HAPA level.

4.3 Agent Simulation

In this section, we examine the design of the agent and the factors that drive the agent behaviour. An Agent, in replicating human activities, starts the day and makes decisions throughout the day. In Figure 4.2, you see the agent looping through the day deciding what to do.

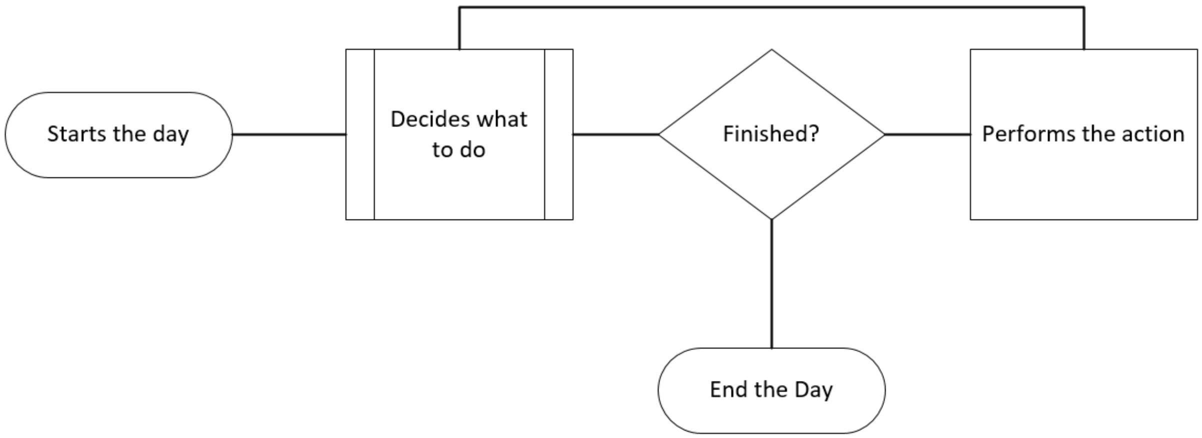

Figure 4.2: Agent Simple Day

In the ABM, we are only concerned with simulating the interactions between the agent and the online SCI community. The following factors are used to drive how the agent will interact with the community: health, personality type, learning style, average online time, tolerance and receptiveness. The simulated day is represented in five-minute cycles, since the activities we are simulating can be time intense as people review material, craft questions, and partake in discussions. The simulation model polls the agent every cycle to see if it is ready to perform another action, given a variety of agent attributes such as usual start time, average usage online, and current availability.

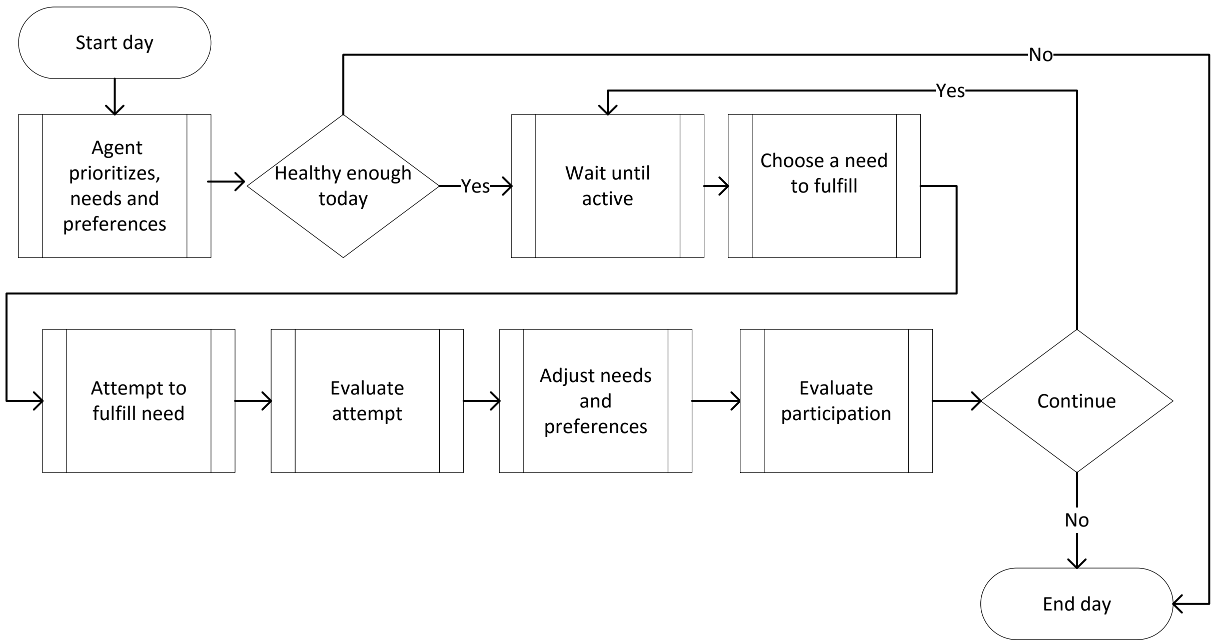

Figure 4.3: Agent steps throughout a day

The daily flow diagram in Figure 4.3 shows the necessary steps the agent will take throughout the day to satisfy its needs. The agent first prioritizes its needs and preferences; then if it is healthy enough to continue they attempt to meet its needs while evaluating its needs and adjusting its preferences, much as we do throughout our day.

4.3.1 Fuzzy Classifier

In Section 2.2.1, we discussed fuzzy logic as a means to make the agents appear more realistic and less deterministic. The interpretation of a fuzzy rule set or defuzzification can be performed in several different ways. The most popular method is the centroid method [60]. The centroid method calculates the center of gravity for the area under the curve. The centroid method is effective across multiple planes, or when boundaries are erratic. The fuzzy classifiers used in this thesis are linear in nature, which can be represented by a simple binary fuzzy de-classifier shown in Figure 4.4. The output of the classifier is true or false and calculated using a variance, and the input value. In Figure 4.4, we see the input value marked by the vertical line at position 50 on the horizontal axis. The variance is used to calculate the true and false hard thresholds from the input value. In this example, a 10% variance each way, gives us a false threshold of 40 and a true threshold of 60. Any number between 40 and 60 are subject to the fuzzy declassification described below.

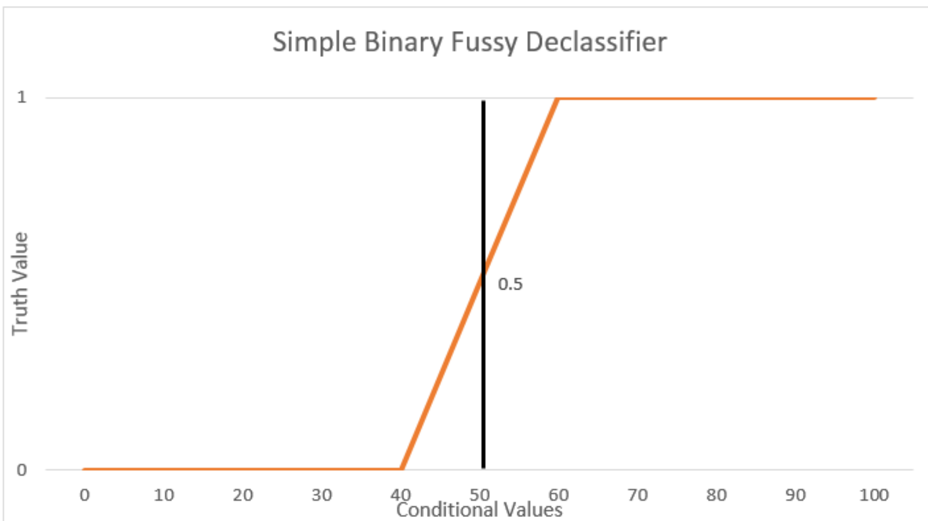

Figure 4.4: Simple Binary Fuzzy Declassified

In this example, we belong equally to the true and false sets. As we move towards the value 60, we become more true than false, which increases our chances of returning true. The fuzzy de-classifier used in the model compares the degree of true to a random number between 0 and 1. The degree of truth is calculated by dividing the distanced between the threshold and the upper limit of a hard false divided by the slope of the line. In this example, the slope of the line is 20; the threshold is 50; and the upper limit of a hard false is 40. This means that the degree is (50-40)/20=50%.

4.3.2 Healthy Enough

The initial factor we chose to drive the agent actions is health. Is the agent healthy enough to even want to login to the community? The SCI community is prone to 2.5 urinary tract infections a year, which can be disabling [61]. We chose to represent health as an individual percentage for an agent that can vary daily. To calculate if an agent will participate that day we compare a random number against its daily health percentage using the fuzzy de-classifier described in Section 4.3.1. The daily health value is the agent average health plus a random variance as shown in Equation (4.3.1). The actual decision shown in Equation (4.3.2) is a fuzzy variable that becomes random close to the Daily Health value as described in Section 4.3.1.

$$\text{Daily Health} = (\text{Average Health} + \text{random variance}); \qquad (4.3.1)$$

$$\text{Daily Heath binary} = \text{Fuzzy Decision (Daily Health, Variance)}; \qquad (4.3.2)$$

4.3.3 Personality

The next factor that we chose to drive the agent actions was personality. A daily personality value is used to drive how the agent prioritizes its needs. The daily personality value is similar to the daily health value in Section 4.3.2, with the added feature of reflection. The flow chart in Figure 4.5 shows how the agent experience adjust its preferences. If an agent had a bad social experience, its daily personality score lower to reflect its bad experience.

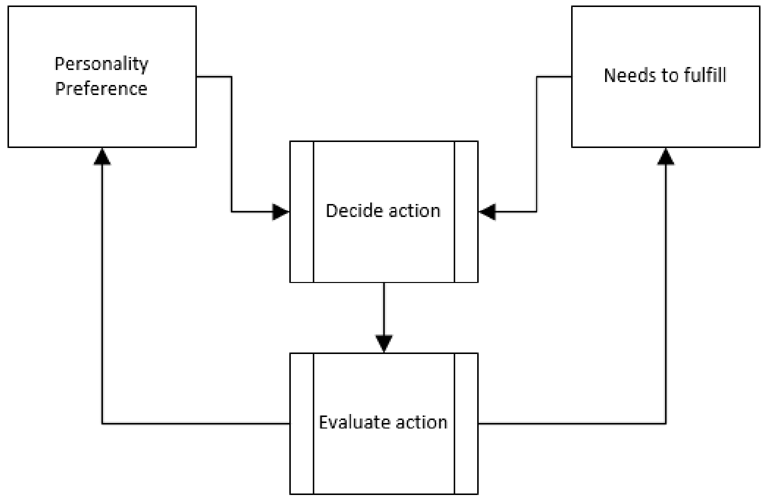

Figure 4.5: Personality Reflection

If the agent is feeling social, then the social features are included in its choices of options to use to fulfill its needs. The Equations (4.3.3) and (4.3.4) shown below are similar to the health variable allowing daily value to differ from its average value and using fuzzy logic to give the agent a more realistic appearance.

$$\text{Daily Personality} = (\text{Average Personality} + \text{Yesterday evaluation} + \text{random variance}); \qquad (4.3.3)$$

$$\text{Social indicator} = \text{Fuzzy Decision (Daily personality, Variance)}; \qquad (4.3.4)$$

4.3.4 Learning Style

The next factor that we chose to drive the agent behaviour is style of learning. A learning value will decide how the agents will fulfil its needs. The daily learning value is similar to the daily health value in Equations (4.3.5) and (4.3.6). If the agent learning style is organized, it will focus on its highest ranked need, rather than try to address multiple needs throughout the day. The higher the learning value the more likely it will focus its highest ranked need each day.

Daily Learning Style= (Average Learning Style+ Yesterday Evaluation + Random Variance); (4.3.5)

Learning Indicator = Fuzzy Decision (Daily Learning Style, Variance); (4.3.6)

4.3.5 Dropout

The final factors that we chose to drive the agent behaviour are acceptance and tolerance that influence participation in the program. The model must account for agents quitting the adoption of a health behaviour and or the community. In the research, we found that people would stop treatment because of excessive treatment time, incorrect treatment, and in some cases for nothing.

The first of these factors is acceptance, which will impact how the agent judges the interaction with the site. In the real online community, the site content is moderated, filtered, and vetted to ensure that the material is suitable for the client. Since most interactions should be positive, we use a simple comparison of an agent acceptance score to a random number to judge if its interaction was beneficial, and update the relevant preferences and results accordingly.

The second factor is tolerance which will impact how long an agent will tolerate negative interactions before abandoning a health behaviour adoption or the program. Tolerance is used to judge both ineffective treatment and excessive time spans. To calculate ineffective treatment, we compare the agent tolerance level against its percentage of successes within a behaviour. To calculate excessive time spans, we examine the time variation between an agent trying to adopt a behaviour against the model averages for each behaviour level.

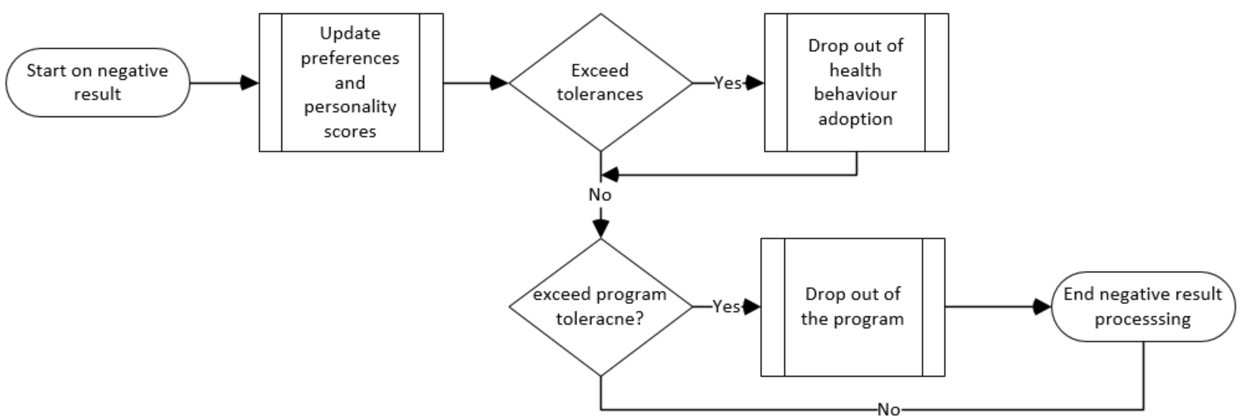

Figure 4.6: Negative Results processing

When an agent receives an incorrect resource due to misclassification, or the agent rejects the material, then the steps in Figure 4.6 are activated. First, the agent updates the preferences and personality scores. Then they check tolerance levels for the given behaviour it is trying to satisfy. If its tolerances have been exceeded they drop everything that is out of tolerance

Finally, to account for an agent dropping out not for the reasons above we use daily random comparison against a drop value for the model. Each agent is tested at the start of the day to see if they will drop a behaviour or the community.

4.3.6 Summary

There are any number of logic, factors, and actions that we could have chosen to model the SCI online community. Our goal was only to model the activities in a realistic fashion to gain an understanding of the benefits, and the potential deficiencies, of automated HAPA classification within an online community. In order to accomplish this, we chose to utilize fuzzy logic, where appropriate, to avoid a binary appearance in the model. Then, we chose to use properties of agent health, personality, and learning style to drive agent actions. Finally, we chose to utilize a random drop out process to simulate non-adherence to attempt to deal with a non-specific set of rationales that are not modeled by research to date.

4.4 Model Design

In this section, we will examine the ABM design, which incorporates the factors and elements discussed above. First, we will examine the agent and then the model in which the agent operates. In Figure 4.7, we see a typical depiction of a SCI agent. The depiction shows the agent interacting with the SCI environment governed by its programmed logic and influenced by its beliefs and attributes which update if necessary following each interaction.

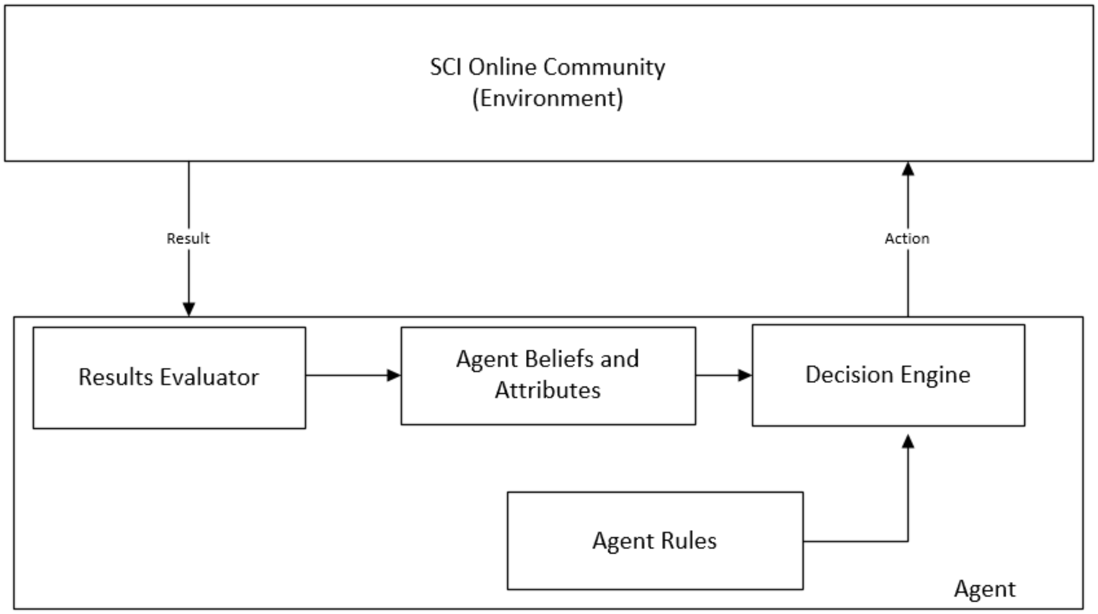

Figure 4.7: SCI Agent

In Section 4.3, we touched on several attributes that the agent uses to drive its actions. These traits can be sub-divided into two categories being personality traits and general characteristics. The personality traits are those attributes you would associate to a person such as: personality style as described in Section 4.3.3, learning style as described in Section 4.3.4, tolerance level and acceptance level both described in Section 4.3.5. Personality traits drive the agent decisions on how to proceed to satisfy their needs. If an agent has a low personality level, they are considered more introverted and are likely to shy away from the social aspects of the online community. The general characteristic are attributes that define their needs and drive the agent actions. The general characteristic are an average health value described in Section 4.3.2, ranking of the HAPA behaviours introduced in Section 1.1, HAPA levels introduced in discussed in Section 4.2, typical start time, average daily use and status that are self-explanatory. To introduce variability into the model, the average health, the personality style and the learning style have daily values that vary from the average values given a random variance. All these attributes are currently loaded randomly when the model is activated using a random number generated with a seed value if available. For instance, the average time spent online as described in Section 2.3.3 is the average of the seed values used to generate the random value that will be assign to the agent upon activation. These attributes being loaded actually simulate the PROs discussed in Section 1.1. If the thesis had actual people being modelled we would be asking them questions about their average health and variations rather than using random numbers.

In the model, the agent only interacts with the online system, which is by design. The URinCharge platform enforces that all interactions are through the online system to maintain a vetted safe environment. The agent can only seek information, share information, form relationships and have online discussions with like-minded people as described in Section 2.3.2. Once the scheduler has activated the agent, it will decide which of the actions it wants to perform to satisfy a need calculated from the agent attributes. The agent will perform the action, which is tracked in the model using a globally unique identifier (GUID). If the agent is trying to adopt a health behaviour and they chose to retrieve a resource, they will be presented with the first resource classified for their current HAPA level for that given behaviour. Upon the next query on the same subject, they will be presented with the next resource classified for their current HAPA level for that given behaviour. The resources are presented in order, until the agent ascends to the next level, or exhausts all the resources for the given behaviour they are trying to adopt at their current HAPA level. If they exhaust all the resources and have not ascended, then negative process flow shown in Figure 4.6 is activated.

The model is programmed in C#, which allows the code to be shared between the model and the actual online SCI community. Although the modelling started with Repast, we moved the agent logic into a C# platform. In addition to promoting code sharing, we achieved full control of the model by using C#. In the initial stages of modelling, we found Repast was quick and easy to use and get started with ABM. However, as modelling became more complex; it eventually became easier to port the logic to C# rather than to continue to troubleshoot issues in the source code.

The ABM model, as stated above, is built in C# and contains the environment described in Section 4.1, an agent scheduler, various log generators, and a module to create Weka ARRF files to enable classification by researchers. Weka is a popular open sourced data mining and machine learning software package [62]. The agent memory and attributes are maintained in a series of corresponding matrixes during the simulation.

The main log files created during the simulation are the client, the GUI and the drop log. These logs record the agent actions, results, and failures during the simulation with related information to simplify analysis for researchers. The client log timestamps the agent actions with the agent personality and learning scores. The GUI log timestamps the results of the agent actions capturing the GUI provided to the agent. The GUI log also records; personality score, learning scores, agent HAPA classification, and system estimated HAPA classification for that agent. The drop log timestamps when an agent drops a health behaviour and or the program. The drop log also records; personality score, learning scores, tolerance score, agent HAPA classification, and system estimated HAPA classification.

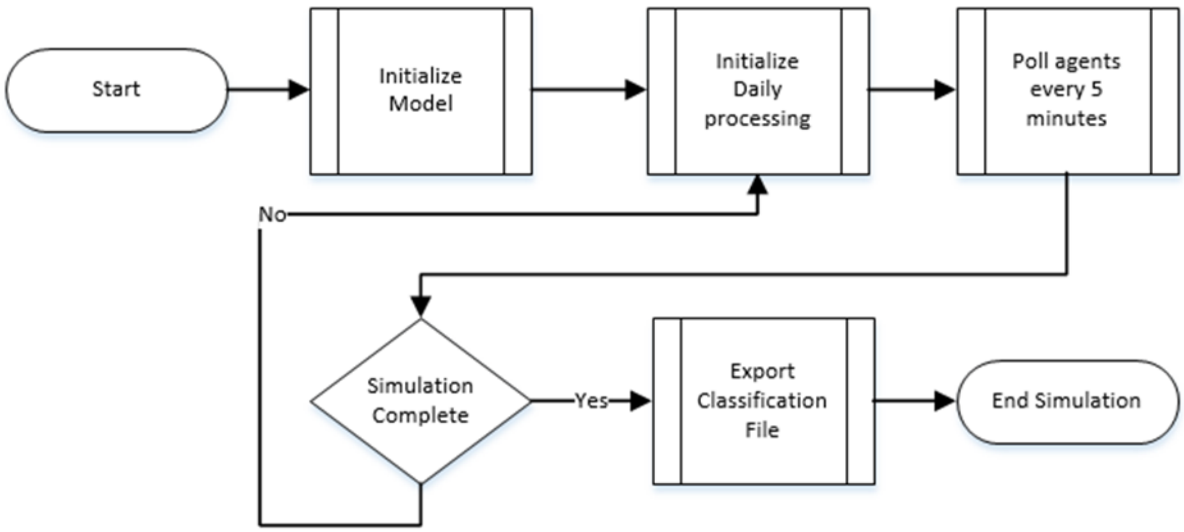

Figure 4.8: Model Flow Diagram

The model flow shown in Figure 4.8 is typical flow for a time-based ABM. The model is loaded and initialized which in this case is similar to administering PROs. Once initialized, the model loops through simulation daily adjusting the agent goals and drivers until the simulation is complete. APPENDIX A contains the pseudo code for the model; the actual code is available upon request.

4.5 Classification

In this section, we describe how the components required for classification are represented in the model and the flow of the classification process. First, we examine how the online community maps into the HAPA framework. Then we discuss the flow of the proposed HAPA classifier since the flow is similar to both the model and the actual online community.

4.5.1 Classification Overview

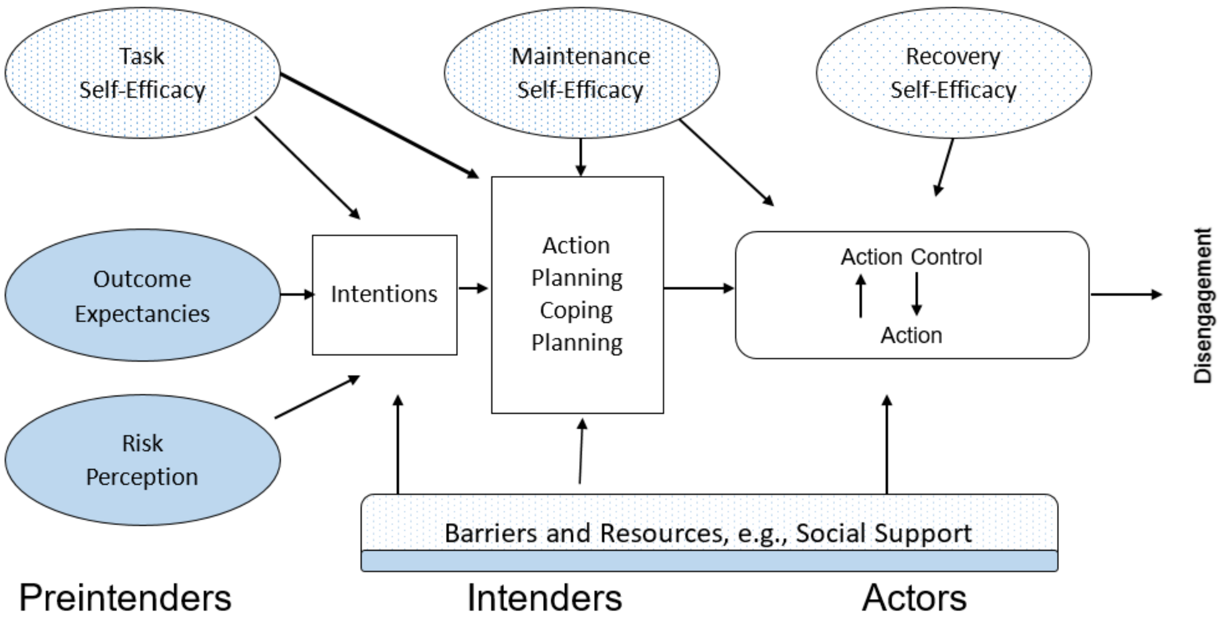

Figure 4.9: HAPA Diagram showing Knowledge and Efficacy Artifacts

In the HAPA diagram in Figure 4.9, several shapes have been filled to emphasize how the online system will address the different influences that affect health behaviour adoption. The online system will attempt to increase knowledge to address the influences shaded in blue and improve Self-Efficacy to address the influences partially filled. The system will use hard artifacts such as pamphlets, articles, forum postings to increase knowledge to affect changes in expectations, perceptions, barriers, and support. The Self-efficacy improvements are being addressed by the online community mostly through the social aspects of the site. There are some resources such as games and videos that can both increase knowledge and self-efficacy. An agent must address all the influences at its current level before progressing to the next level. The actual online community is being set up to increase their client's knowledge and Self-Efficacy surrounding the health behaviours they must adopt.

To perform classification, we must be able to detect that they have sufficient knowledge and Self-Efficacy to proceed. The first part of the equation is accomplished through a categorization process comparing agent activities to other agents that have progressed to the next HAPA level. The classification process is based on the assumption that in the real world a person's motivation and preferences is reflected in their participation and usage. The Self-Efficacy or second part of the equation is accomplished by examining the agent, friends and peers past success.

4.5.2 Classification Flow

The classification engine is similar to most systems that process log information. The proposed HAPA classifier shown in Figure 4.10 would run at night and pre-process the log information into a database which would contain the GUID and Date of access for each client. Once the new daily information has been added to the database, it would be used to calculate if the user has sufficient knowledge to move to the next level using classification. Once the knowledge component is known, it will be combined with the Self-Efficacy score to derive a current level for the client for each HAPA behaviour they are trying to master.

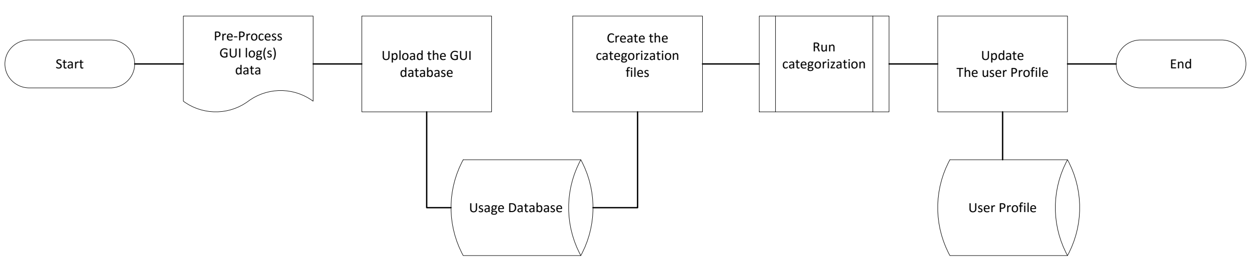

Figure 4.10: Classification Process Flow

4.5.3 Classification Training Set

It is important to acknowledge that this is a first attempt to model a HAPA inspired online community, and there is no existing data suitable for this study. Therefore, as stated in my proposal the output from the model would be compared to logic to validate the model, and a training set would need to be built for categorization simulation.

The training set represents the essential resources or features required before an agent can progress to the next level through classification. To perform classification, we need to create training sets, one for each health behaviour, to avoid crossover since features could be used in more than one behaviour. At this time, we will only be using a simple classifier that would run nightly until real data becomes available. Future studies should be able to improve the online community's effectiveness by using real-time classification schemes.

The entries in the training sets will consist of the same randomly chosen resources with a percentage of noise applied to each entry. In reality, a person's motivation and preferences dictate their participation and usage, which will create several sub-groups within a given HAPA level. In the proposed online community, all the resources will be tagged which will drive the subgroups. At this time, the model is not going to simulate tagging since the addition of subgroups will only increase the simulation time.

4.5.4 Self-Efficacy

The model needs to account for Self-Efficacy since it is a major component of the HAPA framework. Self-Efficacy is primarily a function of your experiences, peers' experiences, social persuasion, and physiological feedback. These factors cannot be easily be measured using online variables and actions. In this section, we describe how we chose to calculate Self-efficacy.

The best indicator of future adoption is past experiences; however, without a client to ask, "We cannot assign a value past experiences". A mastery value assigned, to each agent to represent past experience. The next indicator of importance is the vicarious experiences. We calculate a value for vicarious experiences using agent friendships. To assign friends, we update a friendship matrix as the agent encounter other agents also seeking friendship. Each encounter is evaluated using a simple friendship value compared to a random number. If the encounter was successful, the friendship matrix is incremented. We use a friendship value to assign friends rather than simulate likes and interests, since the model is a simulation of the people interacting with the online community not how they develop friendships. The third indicator of importance is social or verbal persuasion, which can take the form of written material or social pressure. We can simulate social persuasion by using a percentage of their successful peers they met in the community and account for the written material in the knowledge portion of the classification equation. Finally, the least important indicator of Self-Efficacy is physiological feedback; this factor will not be simulated. In the model Self-Efficacy is a function of past mastery experiences, and friends and peers successes and failures as shown in Equation (4.3.7).

$$E=F\,(\text{Past Masteries, Friends Past Masteries, Peers Past Masteries}) \tag{4.3.7}$$

4.6 Summary

In this chapter, we introduced the designs of the core components of our model. We discussed the HAPA online community, the HAPA classifier, and the design of the agents.

In the next Chapter 5, we present our simulation experiment results and an analysis of the simulation results to verify that our model is working as designed and is able to quantify the possible benefits of automated HAPA categorization.

CHAPTER 5

Simulation and Results

In this section, we will discuss how we acquired and then examined the simulation results to verify that our model is working as designed and to quantify the possible benefits of automated HAPA categorization. The main outputs from the simulation are a log of the agent activities required to verify the agent actions. Each simulation run creates a separate log folder containing a summary of agent attributes, a listing of agent activities, a summary of agent successes.

5.1 Data Acquisition

The data used in the model verification and analysis was a combination of client activity logs form multiple simulations. The client activity logs contain the agent actions in addition to its attributes. The log sizes varied between simulation run; however, the average for our configuration was four entries a day per agents. The maximum size could be 288 entries per day for each agent if you chose to configure the model to have the agents always active and perfectly healthy. The logs used in the analysis are described in Section 4.4. The data and model are both available upon request.

5.2 Simulation Validation

To verify the simulation, we will compare our results to a few basic assumptions that can be inferred from the logic programmed into the agent. The first being that the higher the personality type, the more social the agent. The second is that the higher the learning rating, the more globetrotting the agent will do while trying to fulfill their needs. The data from multiple simulations, varying in size, were combined for the verification.

5.1.1 Personality Validation

To verify the model logic for actions related to personality, we expect to see that social activities correlate positively to personality rating. Higher personality rating should result in more social activity; while, lower ratings should result in an agent being less social. Below in Figure 5.1 is a typical trend graph from a simulation run. The graph is a plot of the number of social actions plotted against the agent personality score. The outliers differ between runs, but the trend line visibly shows that the model is performing as designed. The R-squared value of the trend line is only 54%. R-squared is a statistical measure of how close the data are to the fitted regression line. The Equation in (5.1.1) is one minus the error of using x to estimate y. The error is the sum of individual difference squared from the line divided by the individual differences squared from the mean of y.

$$\text{R-squared} = 1 - \sum(\text{Square Error of y to the line}) \,/\, \sum(\text{Square Error to the mean of y}) \qquad (5.1.1)$$

An R-square value of 100% represents a perfect fit between the line and the data. We usually want a higher R-square value except when trying to model human behaviour. Frost states that the R-squared value is field dependent. Projects attempting to predict human behaviour typically have an R-Squared value lower than 50% [63].

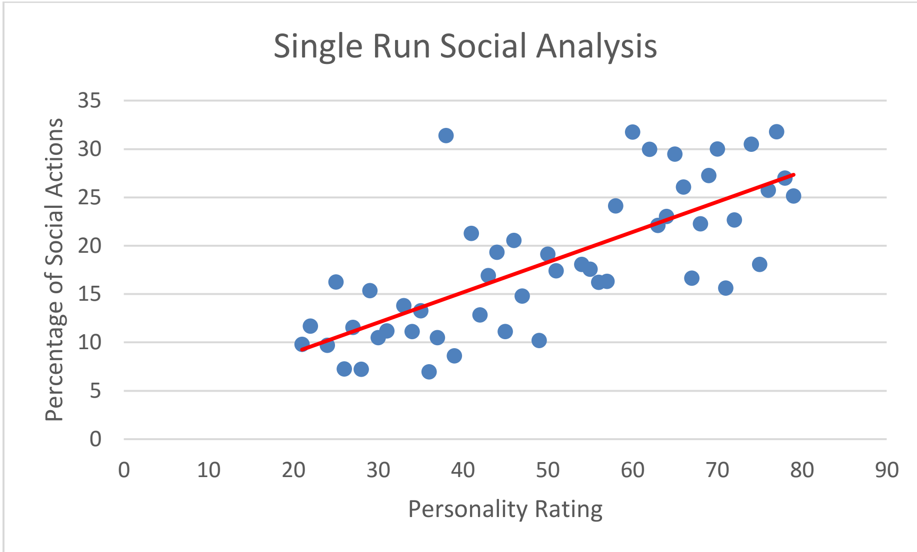

Figure 5.1: Single Run Trend Line Analysis of Social Actions

To explain further the R-Squared value, we examine the outliers. Most of the outlier agents were not as active as the other agents. Agent inactivity represents sickness in the SCI community and relates to the agent health rating. The plot for the personality rating at 38 consists of a single agent. This agent was only active 7% of the time due to a low health rating and was social 31% of the time when it was active. Had the agent had a higher health rating the social activities could have plotted closer to the trend line. The current model uses two decisions points to decide if an agent will be socially active at the start of a session. The first uses the personality formula in (4.3.4) to decided whether to include social options when trying to decide what to do. The second is a random selection from a list of options available to the agent at that time. The use of the two decision point was meant to achieve a more human-like interaction.

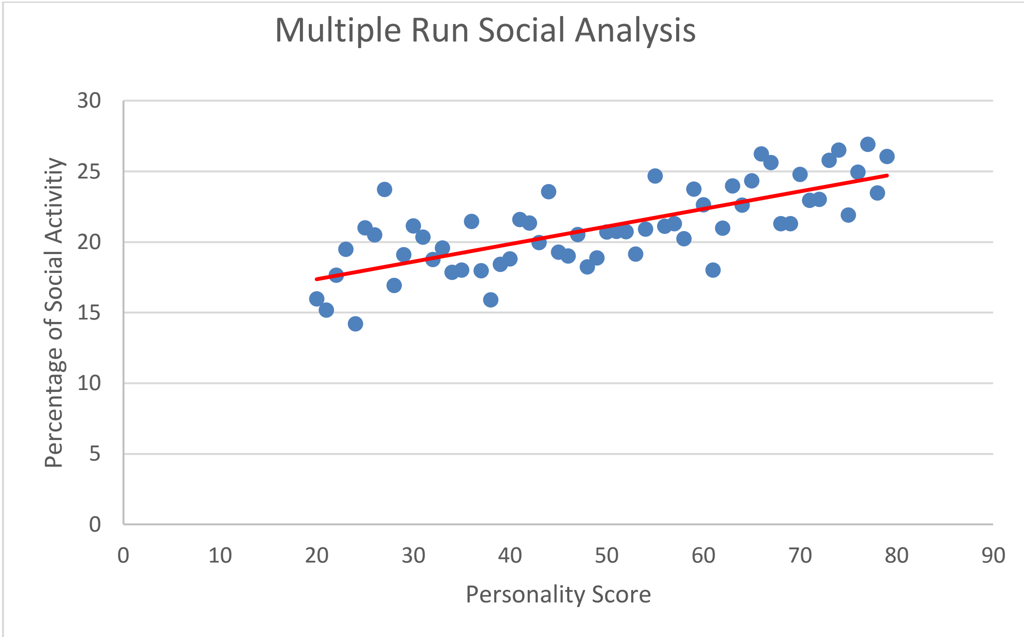

Figure 5.2: Multiple Run Trend Line Analysis of Social Actions

The graph in Figure 5.2 is an average of multiple runs which, at a glance, appears more acceptable than the single run analysis in Figure 5.1. The plots are clustered closer to the trend line; however, the R-squared value is only 55%, which is only slightly better than the single run analysis, hence the improvement is noticeable, although slight.

In this simulation, we find that the personality score does correlate to the social activity. This only proves that the model is behaving as designed. The question still outstanding is “Will personality be a factor in SCI usage of the community.”

5.1.2 Learning Validation

To verify the model logic with respect to learning style, we expect to see that globetrotting correlates positively to learning style. The higher the learning style, the more random the agent is in addressing its health behaviours. Figure 5.3 shows the trend graph created from the simulations where we plot the percentage of globetrotting (i.e. percentage of random learning) against the learning style. We only present the multiple run analysis, since learning only uses a single decision point as opposed to the social activity, which uses two decisions. The single run had an R-square value of 90% while the multiple run analysis had an R-square value of 98%. The trend line strongly shows that the model is performing as designed.

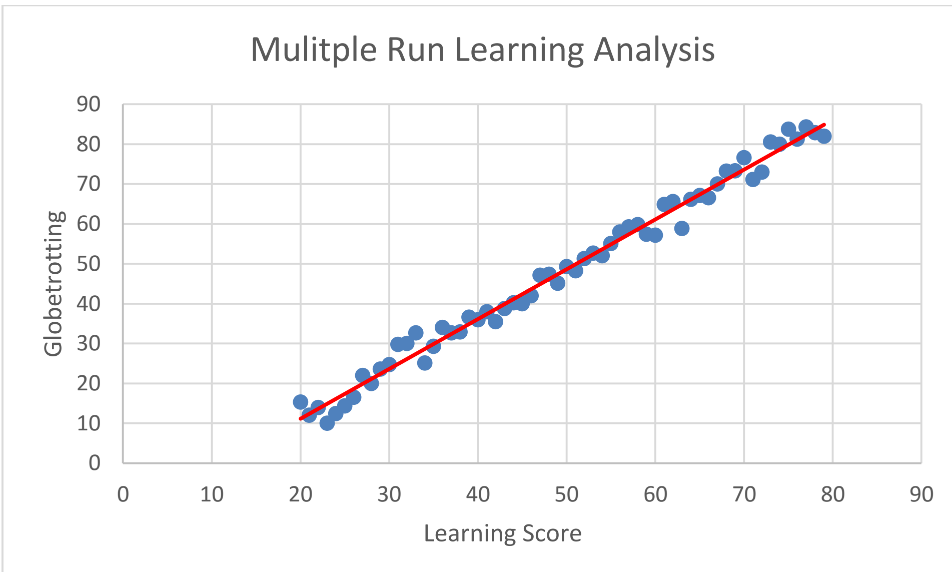

Figure 5.3: Multiple Run Trend Line Analysis of Globetrotting

In this simulation, we find that the learning score does correlate to globetrotting. This only proves that the model is behaving as designed. The question still outstanding is “Will learning style be a factor in the SCI usage of the community.”

5.3 Simulation Output

The simulation data used in this analysis is from simulations of similar sizes to allow us to focus on the averages versus a single simulation. The objectives at this time are to: 1) find when nightly categorization should start; and, 2) quantify the benefits of automated HAPA classification versus bi-weekly manual categorization. To accomplish these objectives, we examined when an agent dropped out and when the agent ascended to the next level from the log data.

5.3.1 Simulation Analysis

The dropout analysis is a summary of the agents who dropped a health behaviour and or the whole program during the first 120 days. The data did not include the agents who randomly dropped a behaviour or the program. The data in Table 5.1 is a summary of various runs showing the first and average day an agent drops a behaviour or program. The table also provides the tolerance statistics of the agents involved. The data provides an insight into when categorization should start, if we want to design a program to catch the outliers.

Item	First Day	Average Day	Average Number	Max Number	Min Tolerance	Average Tolerance	Max Tolerance
First Behaviour Dropped	15	25	1	1	26	35.4	66
Behaviour drops	15	72	140	23	21	43	79
First Program Dropped	28	65	1	1	26	39.8	72
Program Drops	28	82.3	14	3	23	39.7	72

Table 5.1: Dropouts within 120 Days

We see agents dropping behaviours after two weeks and the whole program after two months. Over the course of the 120 days on average 140 agents drop a health behaviour by the 72nd day, and 14 agents drop the program by the 82nd day. Note the average tolerances of those who dropped out were relatively low. You could interpret the data, as “agents with low tolerances are the first to drop a health behaviour do to frustration.”

5.3.2 Categorization Analysis

The categorization analysis is a summary of 100 agents focusing on when agents can start to ascend within the HAPA framework. Note: a simplified training set was used for classification since no training dataset currently exists for the online community. The data in Table 5.2 is a weekly summary of agents who can progress to the next level within the HAPA framework. The table contains data from the simulation runs and shows the minimum, maximum and an average number of agents who can progress to the next HAPA level of a HAPA level of a health behaviour. The results were similar, independent of the training set used. The size of the training with respect to the number of required resources only increased the time before an agent could progresss. The reason for the similar results is because the agent is presented only vetted resources in an ordered fashion. The data in the table was created by analyzing the GUI logs from mulitple simulations and assumed 50 resources per HAPA level and the agent was eligible to acsend upon completing 80% of the resources.

Week	3	4	5	6	7	...	15	Avg.
Minimum	1	2	3	5	5	...	1	3.4
Average	4.8	3	4.8	6	6.8	...	5	5.9
Maximum	8	4	7	7	11	...	4	8.3

Table 5.2: Weekly Categorizations

On average, six agents per week ascend within the framework out of a possible 800 behaviours in this sample. The first three weeks show no movement within the framework; however, the drop analysis shows our first drop out on day 15; therefore, we want to start categorization after the first week starting from a cold start to try to avoid dropouts.

The columns in Table 5.2, show the number of agents who were reclassified during a given week. The shaded columns have been added to show the number of agents that would be classified with bi-weekly classification. The numbers in the unshaded columns represent the agents who are being provided incorrect material while they wait for the system to reclassify them. During week four we have on average three people ready to ascend to the next level who are in danger of dropping out since they will not be classified until week 5. If we look at the averages, you can easily say that bi-weekly classification puts on average about six agents at risk of dropping out because of incorrect classification.

5.4 Summary

In this chapter, we reported on the simulation runs taken in order to acquire multiple run datasets. These datasets were examined in order to verify our model and to gain an understanding of the potential benefits of automated HAPA classification. In terms of verification, we found that the model is performing as designed. With regard to automated HAPA classification, we found that the online community could derive potential benefits.

In the next Chapter 6, we conclude the thesis by reviewing our findings and discuss future work opportunities in this area of study.

CHAPTER 6

Conclusion

We began this thesis by putting the reader in the place of a person who just sustained a spinal cord injury. You woke up in an ambulance, partially paralyzed, following an accident. You will be involved with self-management of your own health, assessing your secondary symptoms for the rest of your life and trying to sustain good health.

The current best practice approach to self-managing behaviour change is referred to as the Health Action Process Approach (HAPA), developed by Ralf Schwarzer. In turn, HAPA utilizes Patient Reported Outcomes (PROs) as measures within self-management programs. Although PROs have been criticized because they are subject to human error [7] [8], they are nonetheless considered an essential part of self-management approaches. In the model we developed, based on computational agents, we simulated the PROs by assigning random numbers to the PRO variables; since no human data was available at this the time of the model. The random number generator used topical seed values when available, to ensure the PRO and other model attributes were representative of the real world.

We began this thesis by examining the relevant research with respect to HAPA and the components necessary to build a simulation model and platform for an online, self-managing SCI community. From this starting point, we designed and implemented an Agent-Based Model (ABM) to model the HAPA approach and, thereby, gain an understanding of the possible benefits of automating HAPA classification within a self-management program. In Chapter 2 we presented the HAPA framework in the context of actual health practice involving human experts and patients, in order to identify primary factors that drive the agents within the ABM. In Chapter 3 we presented our thesis problem, hypothesis, objectives, and methodology. In Chapter 4 we presented the design of the HAPA online community, the logic for the ABM, and the HAPA classification engine.

In Chapter 5 we discussed the simulation results and the benefits of automated HAPA classification. Inasmuch as agents can provide only approximations to real human behaviour, they are still useful and informative. As part of our results, we showed that an automated HAPA classification can reduce the risk of agents dropping a health behaviour or program due to misclassification.

Misalignment occurs when the HAPA levels differ between the agent and online sytem occurs. Misalignment forced the agents to search the site for the correct material, which essentially frustrated the agents, causing them to drop the behaviour adoption. Further, findings revealed that 6% of the agents are in danger of dropping the adoption of an individual health behaviour within two weeks and that 14% of the agents are at risk of at dropping out of the community without continual HAPA reclassification. We also found that bi-weekly manual categorization has the potential to cause dropouts between categorizations because personalization causes misalignments until the system is updated with the correct HAPA stages. Dropouts can still occur with nightly automated classification, but the risk is much smaller for those agents who are less tolerant. The results are of the simulations are only an indication of what could be if the misalignments also occur in the URinCharge system. As mentioned further below, live classification and misalignment detection should be investigated once real data becomes available; we know already that the URinCharge research project is utilizing PROs and those can be inaccurate, as discussed in Section 1.1.

Finally, our contributions to Computer Science include: a simple binary fuzzy de-classifier as described in Section 4.3.1, and, as we do not operate in a vacuum, we introduce a HAPA state diagram and methodology to support patient self-management, described in Section 4.2. HAPA serves as an inspiration for health self-management architecture design, real-world patient interaction and a foundation to study model design and simulation using agents. Our work also facilitates co-operative work with the Health sector.

6.1 Future Work

Among the future directions for further work that needs to be explored in this area, we include: 1) verify the model using data from actual SCI online communites to allow for more in-depth analysis in the real-world context; 2) investigate real-time HAPA categorization once actual data is available for accurate validation; and, 3) examine methods for detecting misalignments between a person's real HAPA stage and the system-assigned stage to reduce early behaviour adoption dropouts.

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APPENDIX A

In this Appendix we present the pseudo code used to develop the model. The actual code is avaialable upon request. The code consist of four main modules that control the agent activities.

A.1 Main Simulation

The main simulation initialises the model and then loops througth the simulation day by day, polling the agent every five minutes to see it they are prepared to execute the agent logic.

```
// Start the simulation
 InitializeModel();              //load the agent attributes, AKA PROS
// loops throught the days
while (DayCount < Stopday)
{
        IntializeDaily();        // intialize daily attributes, AKA adjust the PROS
        // loops throught the day
        for (Timeofday = 1; Timeofday < 289; ++Timeofday)    // check every simulated 5 mins
        {
                Check Health();          // Verify agent is health enough to continue
                Get Currnet Goal();      // Agent decides action to take.
                Preform Action();        // Agent preforms action
                Increment Time ();
        }
        Increament Day(); }
```

A.2 Initialize Model

The agent attributes are set in this module, which represent administering a PRO questionnaire to drive the agent behaviour. At this time, there is no data set available for this research as described in Section 4.4.

```
// Initialize Model

ForEach Agent {
        DailyMaxAction[agent] = random.Next(3, 60);    // Amount of time online
        Starttimer[agent] = random.Next(0, 260);       // Agent starts on the Nth timeslot.
        Nexttimer[agent] = Starttimer[agent];          // Set next action to start slot
        Lstyle[agent] = random.Next(20, 80);           //Set Learning score
        Ptype[agent] = random.Next(20, 80);            // Set Personality Score
        Health[agent] = random.Next(20, 80);           // Set Agent average health
        Tolerance[agent] = random.Next(20, 80);        // Set Agent average Tolerance
        // Assign HAPA ranking and classification
        // Ranking of Categories 0 -99 to give indication of importance
        // Vary HAPA classification between agent and system to simulate misalignment.
        ForEach HAPAissue {
            HAPArank[agent, issue] = random.Next(1, 99);          //Assign HAPARank
            HclassEst[agent, issue] = HclassInt[agent, issue];    //Load HAPA Estimate
             // Randomly create misalignment on Hclassrr percent of agents.
             if ((random.Next(0, 100) < HclassErr) && (HclassEst[agent, issue] > 0))
                { HclassReal[agent, issue] = HclassEst[agent, issue] - 1; Misalignment++; }
        }}
```

A.3 Initialize Daily

The agent attributes are adjusted daily to account for variations from the agent average values. The model daily counters are also reset.

```
// Initialize day
ForEach Agent {
        Reset counter();                // reset daily hit and miss counters
        // vary health, personality and learning score by a ranbom variance from average
        DailyHealth[agent] = Health[agent] + random.Next(dailyvar * -1, dailyvar);
        Dailyptype[agent] = Ptype[agent] + random.Next(dailyvar * -1, dailyvar);
        Dailyltype[agent] = Ltype[agent] + random.Next(dailyvar * -1, dailyvar);
        Set Daily Main Goal();          // seek info, share info,
        }
```

A.4 Get Resource

When an agent decides that it needs to get information on a HAPA behaviour throught reaserch the following is executed. The daily lerning score is used to decide which behaviour is will be researched. If the agent is a globtrotting as described in Section 4.3.4 the topics will be selected at random verus focusing on the HAPA behaviour with the highest ranking.

```
 //Get Resource
Select the Topic();              // if globtrotting select topic at random
Increament Nexttimer();                 // assume correct resource will be provided
Get next resouce based on system HAPAlvl();       // based on last resource provide to agent
If (HAPAlvl <>HAPAest ) {
```

```
    Get resource based on Agent HAPAlvl();     // based on last resource provided to agent
    Increment NextTimer();                     // add additioinal time to account for search
    Increment MissCounter();           // update counters
    CheckTolerance();                  // check Tolerences and drop topic if required
}
Else {increment HitCounters();}}       // update counters
```

VITA AUCTORIS

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