

Exploring Computational Models for Intelligent Support of Persons with Depression



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VRIJE UNIVERSITEIT

Exploring Computational Models for Intelligent Support of Persons with Depression

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door

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Abstract

In many occasions, feeling depressed is a common human experience, occurring most often as a normal response to external events. However, if this feeling takes hold and will not go away, it may become a unipolar depression. Persons with a depressive illness cannot merely ‘pull themselves together’ and get better. Normally they may feel sad, anxious, hopeless, worthless, irritable, or restless. These conditions can become chronic and lead to substantial impairments in an individual's ability to take care of his or her everyday responsibilities. In some serious cases, they even may contemplate or attempt to commit suicide. Therefore, it is important to understand the development of depression in order to support depressed persons. As a first step to address the quest to help persons with depression from a computational perspective, this thesis explores a number of computational models that may be embedded in ambient agent models. These computational models are based on related theories to explain various observed aspects and conditions for depressed persons. For example, mathematical definitions and computational implementations are provided for relapse, hopelessness, social support interaction, and mood contagion. These computational models are integrated in ambient agent models, specifically to provide in-depth analysis of the human's functioning (during depression) related to his or her environment and provide support that may more effectively improve his or her wellbeing. From the developed models, a variety of simulation experiments was conducted. Finally, using the simulation traces generated in the experiments, the models were evaluated, in order to verify whether they satisfy a number of essential characteristics and patterns described by particular theories in the literature.

Samenvatting

Een depressief gevoel is een veel voorkomende menselijke ervaring, die zich meestal voordoet als een normale reactie op externe gebeurtenissen. Echter, als dit gevoel niet meer verdwijnt, kan het een unipolaire depressie worden. Personen met een depressieve aandoening kunnen zichzelf niet gewoon 'bij elkaar rapen' en beter worden. Ze kunnen zich verdrietig voelen, angstig, hopeloos, waardeloos, prikkelbaar, of rusteloos. Deze situatie kan chronisch worden en leiden tot aanzienlijke beperkingen in het vermogen van een individu om te zorgen voor zijn of haar dagelijkse verantwoordelijkheden. In sommige ernstige gevallen kunnen ze zelfs overwegen of proberen zelfmoord te plegen. Daarom is het belangrijk om de ontwikkeling van een depressie te begrijpen en op basis daarvan een depressieve persoon te ondersteunen. Als een eerste stap om de uitdaging aan te gaan om personen met een depressie vanuit een computationeel perspectief te helpen, beschrijft dit proefschrift onderzoek naar een aantal computationele modellen van verschillende aspecten van depressies die kunnen worden ingebed in ambient agent modellen. Deze computationele modellen zijn gebaseerd op theorieën met betrekking tot deze aspecten van depressies. Zo worden bijvoorbeeld definities en computationele implementaties beschreven voor de terugval, uitzichtloosheid, sociale ondersteuning, en wederzijdse besmetting met negatieve stemmingen. De computationele modellen zijn geïntegreerd in ambient agent modellen, zodat die agents een diepgaande analyse kunnen geven van het menselijk functioneren bij depressie en de ondersteuning kan geven die iemands welzijn zouden kunnen verbeteren. Op basis van de ontwikkelde modellen is een groot aantal simulatie-experimenten uitgevoerd. Ten slotte zijn de met behulp van deze simulatie-experimenten gegenereerde traces de modellen geëvalueerd, door te verifiëren of ze voldoen aan een aantal essentiële kenmerken en patronen zoals beschreven door bepaalde theorieën in de literatuur.

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After four years of struggles, all I can say is, a doctoral thesis to a certain extent is a little brick that contributes to the great wall of scientific knowledge, a mirror reflecting the strengths (and the weaknesses) as a researcher, and an ode to the never-ending quest of the scientific frontier to decipher the unknown. It is also a solitary undertaking and yet it is difficult and almost impossible, (especially when you are 6278.07 miles away from your comfort zone) to complete without the help and support of many.

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Anyone I might have forgotten, let me know how I can make it up for you :-)

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Part I

Introduction

Chapter 1

Introduction

“Socrates said he was the midwife to his listeners, i.e. he made them reflect better concerning that which they already knew and become better conscious of it. If we only knew what we know, namely, in the use of certain words and concepts that are so subtle in application, we should be astonished at the treasures contained in our knowledge.”

(Immanuel Kant, “Vienna Logic”)

Introduction

As intelligent support technologies take on an increasing role in health care (especially in mental care fields), they must be able to understand a human's functioning process (e.g., psychological state), and provide actions appropriate to the estimated condition of the person. The emerging fields of ambient agents, computational modelling, and cognitive theories have recently reached the point where such models can be designed and studied to see the effects of support for depressed persons by the means of computational models. This raises an important question of how to design such technologies that are able to support depressed persons. To address this issue, in this thesis we explore computational modelling approaches for an ambient agent to provide intelligent support for persons with unipolar depression. We design and evaluate a number of formal models (domain models) to explain different conditions in depressed persons based on empirically grounded literature in psychology. Next, it is explored how these domain models can be integrated with support models using a generic framework for an integrative ambient agent model. These support models utilize important concepts about supports and therapies for depressed persons.

The course of this chapter is as follows. We begin by introducing our research motivation in Section 1. It is followed by a description of unipolar depression (Section 2). In Section 3, we then describe related therapies and social support networks for depressed persons. The essence of computational modelling is discussed in Section 4. Section 5 covers important aspects in ambient agent models. Next, in Section 6 we explain our research objective in this thesis, which includes research questions. Section 7 explains our research approach (methodology and related domains) (Section 7) and Section 8 describes our research scope. Finally, Section 9 points to the origins of the embedded papers.

1 Motivation

Depression was identified in the WHO report as the leading global cause of years of health lost to disease in both men and women. According to the study, unipolar depression made a large contribution to the worldwide burden of disease and associated with the loss of about 850,000 lives every year [29]. It includes its role as the eighth leading cause of loss of health in low-income countries and the primary cause of loss of health in middle and high-income countries [44]. To make it worse, it is estimated that 96 million people with unipolar depression remain untreated worldwide [6]. With the demanding and stressful modern life, it is important to highlight that a person with depression

histories needs support from others to thrive against the relapse. However, in our society, many cannot get the support they need. Especially in developed countries, human population becomes more mobile, individualistic, and fractionated, thereby individuals suffering from depression may find it more difficult to get the support needed to lead mentally healthy lives. Hence, it is equally important to provide several alternatives and options to bridge the gap between the availability of professional support, social support, and self-help. In addition to this, the technological advancement in computer science and engineering also motivates us to pursue this research. For example, for the past decade, a variety of technologies such as wearable sensors [15][19][25], ambient intelligence [7][21], computational modelling [18], and software agents [20] have been used to bring forward a system that can provide support for depressed persons.

2 The Problem Domain: Unipolar Depression

Personal ups and downs are appropriate responses to the difficulties of life. For most people, a period of sadness passes quickly in which it is not severe enough to interfere with normal lifestyle or ability to function. However, some people experience emotional extremes in mood, and they ride an emotional roller coaster with dizzying heights and abysmal depth even when the world around them remains on balance. In an extreme case, they may lose interest in most of their activities and pursuits, having difficulties to concentrate, become physically agitated, and even having a thought of death that may lead to suicide attempt. These conditions are some examples of major symptoms for a mental disorder which is known as a “unipolar depression”. The diagnosis of unipolar depression is based on the occurrence of one or more depressive episodes in the absence of a history of depression. In a unipolar depression, the person experiences either depressed mood (sad or hopeless) or loss of interest in all activities for a period of at least two weeks [41]. If it is untreated, it can result in disability and even death. It tends to be episodic, and of varying severity.

In severe cases, many depressed persons have other concurrent physical and mental disorders. It was estimated that, one in six persons have an episode of depression during their lifetime. Another review showed that the annual prevalence rate of depression is approximately 5 percent in Europe [31]. In addition, depression produces substantial economic costs, both through costs of health and social care, and from other costs such as work days lost. For example, the economic cost of depressive illness was approximated to be 30 to 44 billion dollars a year in the United States, 950 million euros in the Netherlands, and 9 billion pounds in the United Kingdom [13][36]. In addition to this, unipolar depression may also affect those who care about the depressed person, by

destroying family relationships or positive work dynamics between the person and others.

2.1 Lessons from the Unipolar Depression: Relapse and Recurrent

Unipolar depression is often a chronic, disabling and most frequently characterized by relapses and recurrences. One of the major risk factors for repeat episodes (either relapse or recurrence) is the presence of negative symptoms that persist after an episode ends and these negative symptoms tend to progress over time to another major depressive episode [41]. One of the research findings has shown that the majority of patients who have major depressive disorder will experience relapses and recurrences, with the first few episodes linked to unequivocal stressors and later episodes appearing more spontaneously [39]. Relapse can be defined as an episode of a major depressive event that occurs within 6 months after either response (improvement) or remission (full restoration), while recurrence is defined as, another depressive episode which occurs after 6 months have elapsed [30]. It is worth mentioning that many researchers have confirmed that response is defined as a 50 percent improvement in a baseline depression rating scale score [30][33]. Figure 1 shows the phases of relapse and recurrence in unipolar depression.

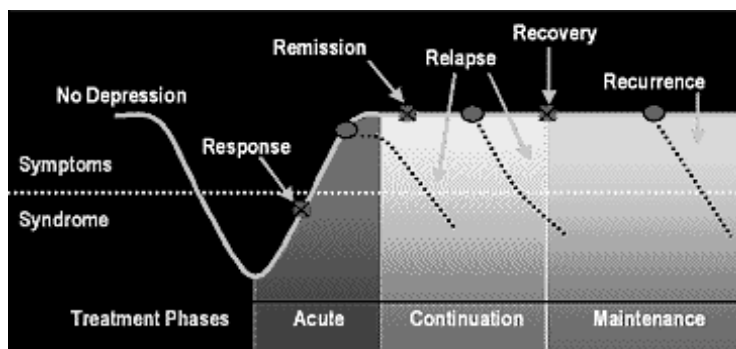


Fig. 1. Diagram of the Five Possible Outcomes across the Three Phases of Treatment in the Clinical Depression (adopted from [41]).

It should be noted that while the Figure 1 perhaps suggests that relapse during the acute phase is more severe than a relapse or recurrence during the continuation and maintenance phase, this may not always be the case. Figure 2 illustrates the interaction of these interrelated concepts.

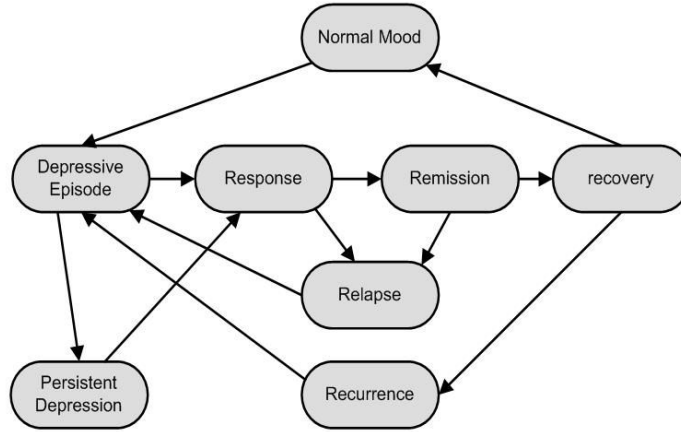


Fig. 2. Conceptual Diagram of the Relationships between Patient's States in Depression.

The conceptual model above depicts the various states that a person may pass through during depressive and recovery events. In this case, we coin the term 'normal mood' to represent a person's health state while he or she is free from depression. From the normal mood state, a vulnerable person will enter a depressive episode, which may lead to two consequences, namely response state and persistent depression. Generally, a person who responds to the treatment offered moves to the response state. However if a person does not respond to the treatment then he or she moves from a depressive episode state to a persistent state. A person could in time move to an improved health state, or suffer from a chronic depressive episode. If a treatment is effective, then over time the individual's status can move from response to remission, and recovery. If during a response or remission state they fall back into a depressive episode, then they have 'relapsed'. If they progress to the recovery phase (e.g. six months after the depressive episode) they are held in this phase (recovery) for several years until returning to a normal mood [41].

Although some people who experience an episode of unipolar depression once will never have another episode, the majority of people with unipolar depression will have additional episodes during their life. About 75 percent of those who experience an episode of unipolar depression will have at least one more episode in their lifetime [24]. This scenario is even worse for patients who have been depressed for several times; such risk of recurrence and relapse seems to have a positive correlation with each successive episode [6][24]. That is why some patients are recommended to continue antidepressants for four to six months after remission to prevent relapse [6]. There are also cases where

people need to take medications for longer periods up to the rest of their lives. Therefore, it is obviously important that rather than managing relapse or recurrence, the best strategy that can be used is to prevent these repeated depressive episodes from occurring in the first place.

3 Related Therapies and Social Support Network for People with Unipolar Depression

A proper treatment for unipolar depression depends on the diagnosis from the medical professional. In cases where the depression is caused by brain chemistry imbalance, anti-depressants may be prescribed. On the other hand, in cases where depression is triggered by social or psychological factors, psychotherapy may be suggested. In addition to those recommendations, a social support network also plays an important role to provide support for depressed persons.

3.1 Cognitive and Behavioural Therapies

Cognitive therapy exploits a group of cognitive techniques altering the abnormal thinking; it uses verbal techniques rather than behavioural approaches [31]. This type of therapy seeks to help the patient overcome difficulties by identifying and changing dysfunctional thinking, behaviour, and emotional responses. In different types of cognitive therapy, patients are required to perform behavioural tasks by carrying out actions that are chosen based on the way they think [40]. These types of therapy can assist the depressed person in several ways. First, it helps alleviate the pain of depression, and addresses the feelings of hopelessness that accompany depression. Second, it changes the negative ideas, unrealistic expectations, and overly critical self-evaluations that create depression and sustain it by assisting in recognizing which life problems are critical, and otherwise. Third, it amends the areas of the person's life that are generating significant stress, and contributing to the depressive state.

In short, the therapies aim to develop better coping skills to reduce cognitive vulnerability towards incoming stress factors. There are several cognitive therapies to help vulnerable and depressed people, for example; Cognitive Behavioural Therapy (CBT), Mindfulness-based Cognitive Therapy (MBCT), Acceptance and Commitment Therapy (ACT), and Rational Emotive Behavioural Therapy (REBT). Some of these techniques are used as foundations for the intelligent support technologies. The details of those techniques will be dealt in the embedded papers.

3.2 Social Support

Social support is something that most people perceive to be useful in many situations when individuals are trying to cope with depression or simply deal with negative events. Our relationships with family, friends, and even acquaintances can have positive effects on our physical and mental health through various types of social support that they offer to us, including instrumental support, emotional support, informational support, and companionship support. Thus, the presence of social support significantly predicts the individual's ability to cope with stress [4]. Knowing that they are valued by others is an important psychological factor in helping them to forget the negative aspects of their lives, and thinking more positively about their environment [14]. Social support is often associated to the concept of a social network, such the ties to family, friends, neighbours, colleagues, and others of significance to the person. A social support network is different from a support group, which is generally a structured meeting run by a mental health professional. Although both can play an important role in times of stress, a social support network is something that can be developed even not under stress, providing the comfort of knowing that support members are there if needed.

In a number of cases the types of supports when facing stressful situations can be useful to one person, but not to other [11][26]. Depending upon the situation, support recipients may perceive some types of support negatively, and this may reduce the positive effects of the supportive effort [26]. Moreover, this condition may eventually escalate the negative impact of stress towards support recipients. For example, receiving informational support from unwanted and non-credible people during times of stress can also be seen as inappropriate. Another example is, a person may interpret negatively any instrumental support for routine and physical tasks, perceived as undermining his or her competency [11]. In this thesis, several important effects of dynamics interactions (during a support provision and receipt process) between a depressed person and his or her social support networks are explored.

4 Computational Modelling

Computational modelling is a process to simulate a set of processes observed in the natural world in order to gain an understanding of these processes and to predict the outcome of natural processes given a specific set of input parameters. It is intended to mimic some essential features of the studied system while leaving out inessentials. Computational models are invaluable because they allow scientists to investigate detailed relationships that could not be sorted out by purely experimental methods, and to make approximations that cannot be made easily by extrapolating from the available data [17].

4.1 Why Bother to Model?

Often, computational model provides a means of risk-free exploration in complex, critical, costly, time-consuming, or rare situations. A constructed computational model is capable of simulating certain key behaviours in the selected domain of interest. For example, in a neuroscience domain, theoretical neuroscientists use computational modelling to help explain and understand the mechanisms of cognition. This means developing explicit mathematical models of the processes that go on in the brain when we perceive, act, learn, think or remember certain tasks. Despite the development of powerful brain imaging machines and software that allow scientists to investigate into greater details of our brain activities, these technologies still fall short to explain the detailed interaction between all of those activities involved [17]. Thus, such use of computational models is regarded as a tool for internal and external investigation of cognition within brain activities.

Another important point is “Hawthorne Effect” may affect the experimental results. It is common that when people feel they are being observed, they will modify their behaviours [32]. Therefore, it may be very difficult to preserve the same condition for each different setting of the experiment. Scientific understanding also drives the use of computational models. For instance, if a computational model embodies a hypothesis about an observed system then it will allow scientists to simulate several conditions to see the possibilities of considering the pre-defined hypothesis. In other words, if a hypothesis fails a test, it can be rejected without taking trouble to do more of the unnecessary experiments. The size of experiments and curse of dimensionality also play central roles why scientists choose to develop computational models. When the experiments of an observed system are infeasible, computational models can be designed using the processes studied by smaller sized experiments and then used to derive the large-sized effects [16]. From a number of perspectives explained above, we suggest that computational models are a good alternative when real world experiments are not practically feasible to be conducted.

4.2 Practical vs. Theoretical Computational Models

Although computational models are used for many possible reasons, we can classify them under two main objectives; *theoretical understanding* and *practical applications*. From a theoretical model standpoint, one can understand how the real system operates. On the other hand, a practical model enables the prediction of the real system by which it will play a role in deciding feasible sets of action [17]. In an extreme case, theoretical models are usually expressed in dynamic equations yet they are often simple enough for scientists to comprehend the underlying process. It is useless to replace an observed system with a complex

model that difficult to comprehend when it has not increased our deeper understanding of the observed domain.

In contrast, practical models normally sacrifice simplicity in order to offer more detailed and precise predictions for an observed system. Thus, practical models are often too complicated and only dedicated for computer simulations [17]. In this connection, it should also be mentioned that practical models entail detailed numerical accuracy, whereas this is not the case in theoretical models. Therefore, the details of the processes can be ignored only if it has less implication in achieving a better numerical accuracy. However, in theoretical models, the details of the processes can be left out if they are conceptually irrelevant to address important theoretical issues. In this thesis, we used both concepts in our models.

4.3 Computational Psychology

Psychology is a study of human mind and behaviour in both applied and academic fields [18]. Research in psychology seeks to understand and explain the theoretical framework of thought, emotion and behaviour. Most of the human psychological processes are very difficult to understand solely based on behavioural observations, especially when the underlying grounding theory of the observed conditions is not fully comprehended [34]. In addition, given the complexity of the human mind, and its effect in behavioural flexibility, it leaves a restricted option that only computational modelling can illustrate the process and its interactions. Moreover, computational modelling can go deeper in terms of level of process details and granularity of input-outputs interactions, which are essentially useful to explain the level of cognitive functions.

Recently, computational models are frequently used as tools for investigating human behaviours and cognitive functions [12]. The models have been used to explore the essence of psychology and various cognitive functionalities through the ongoing detailed understanding by specifying corresponding computational models of representations and mechanisms. It has demonstrated that computational models have succeeded to simulate related behaviours in specific domains of interests by assigning the corresponding computational processes onto cognitive functions to produce executable computational models by which the detailed simulations are performed. Results from the simulations are used to justify that the models offer good explanations of the cognitive mechanisms pertinent to the corresponding domains of interest. Despite the approach of utilizing computational psychology to understand human functioning is relatively new compared to typical behavioural investigations, there have been a few success stories of computational psychology modelling in a practical as well as in a theoretical perspective. They include, among many others; computational models of child development [12], autism [43], symbolic cognitive architecture

(SOAR and ACT-R) [27][38], emotion [9][28], theory of mind [34], post traumatic stress disorder [5], obsessive-compulsive disorder [37], depression [10], and visual attention [8][35].

5 The Integrative Ambient Agent Model: The Intelligent Support

Agent-based and ambient intelligent systems are among the most vibrant areas of research and development to have emerged in computer science. According to [20], an intelligent agent is a computer system that is capable of flexible autonomous action in dynamic, unpredictable, and open environment, whereas ambient intelligence is an innovative paradigm in which people is empowered through a digital environment that is aware of their presence and context and is sensitive, adaptive, and responsive to their needs [1]. The combination of these two areas provides new technological opportunities to contribute to personal care for health, safety, and wellbeing.

5.1 Human Functioning Knowledge within Ambient Intelligence

Knowledge about human functioning is naturally compatible with the notion of ambient intelligence. This in fact highlights the essence of human-related knowledge (e.g., human functioning) to better support the users of the ambient system. Here, human functioning knowledge can be described as a set of knowledge to recognize and predict the current situation in a human's mind, and physiology conditions by observing the human's state over time [42]. In many application areas, the dynamics of the human functioning over time plays a central role. Imagine in the case of unipolar depression, if the patients experience some random and short-term stressful events, the corresponding ambient agent will not intervene immediately. However, when these circumstances repeat in a prevalence pattern, the agent will analyse and provide appropriate support to the patients. Without this human-related knowledge, the underlying intelligence of an ambient agent is limited, and unable to reason accordingly.

The knowledge about human functioning can be presented in static or dynamic forms. However, due to the dynamic interactions between humans and environment, viewing human functioning as a static process is not realistic compared to viewing it through a dynamic form which can be captured based on relevant grounded theories in psychology. As a result, such an ambient agent is equipped with the capability to carry out a more in-depth analysis of the human's functioning related to its environment and provide supports that may more effectively to improve his or her wellbeing [42].

5.2 Knowing How and When to Support

One of the challenges for designing ambient agent models is to provide the right working knowledge that covers vital aspects of providing the right support for depressed people. In the case of unipolar depression, professional practitioners (psychologist) will first diagnose the severity of the depression by analyzing patient's current circumstances, biographical history, current symptoms and family history. In some cases, a medical examination and selected investigations are needed to accommodate other causes with ambiguous symptoms. For example, blood tests to exclude metabolic disturbance, or adverse affective reactions to medications, and a full blood count rule out a systemic infection or chronic disease [6]. If the diagnosis result for depression is positive, the contributing factors of the depression can be identified and the professional practitioners offer patients the appropriate techniques to deal effectively with the psychological, behavioural, interpersonal and situational causes. With that, the depressed patients can identify options for the future and set realistic goals that promote enhancements of their mental and emotional well-being.

Psychologists also help the individuals to identify how they have been successfully dealt with similar feelings, if they have been depressed in the past. In severe cases, some health care practitioners treating depression are in favour of using a combination of psychotherapy and anti-depressant medications. In addition to that, social support networks also contribute to maintain the well-being of the patients and in the same to prevent future relapse or recurrent cases [11][14]. Given the complexity of the standard practises to support depressed individuals, it is a great challenge to design an ambient agent that is capable of having an approximately comparable capability in providing support. Generally, it involves several interrelated areas (e.g. psychology, electronic engineering, and computer science) to design such capability in an ambient agent [2][3]. For example, pervasive sensor information (heart rate variability, pills intake, alcohol level, social interaction via mobile devices, and sweat) can be coupled with a computational model of human functions to serve that purpose [18][22][23][45].

6 Research Objective

The main research objective of this thesis is the modelling of integrative ambient agents that can generate human-like behaviour and intelligent supports for depressed people, specifically in a unipolar depression. To achieve this, we consider three research questions of this thesis.

Research Question 1

(R1): "How can theories from psychology about relevant aspects of depression be represented using computational models?"

Computational models have been proposed as a tool for studying important elements such as humans and their environment during stressful events. However, in order to represent those elements in computational models, we need to have an overview of the relevant aspects of cognitive and psychological perspectives about human's mind and physiology activities, particularly those studied in the theories and literature. In this connection, it is also worth mentioning that computational models usually are representations of the entire real-world conditions of a limited number of relevant aspects. However, having those computational models with related grounding theories; it provides detailed insights to explain the underlying mechanism behind selected processes. Therefore, we hypothesize that it is a good idea to incorporate these computational models within our ambient agents. Therefore, we start to investigate the following research question.

Research Question 2

(R2): "How can ambient agent models to support depressed persons be designed using the developed computational models?"

Besides developing computational models for depression based on corresponding theories, we would also like to model an ambient agent that support people with the risk of depression. To explore this possibility, the integration among a computational model, a support model, and a belief about the human conditions and environments must be carefully designed and evaluated. This is required because the agent must be able to predict human's conditions and to reason the provided supports. Another important point to be taken is the evaluation of patient's conditions after receiving selected supports from an ambient agent. Therefore, we explore another question to address the issue.

Research Question 3

(R3): "How can we evaluate the appropriateness of the domain models and support models?"

Model evaluation is the process of ensuring that the conceptual description and the solution of the model are implemented correctly. The first step is to make sure that the model reflects the real world. For instance, if the behaviours of the system of interest are linear, then those linear behaviours must be reflected in the formal specification underlying the model. To address this question, we investigate both local and global properties of the models and evaluate these properties with important characteristics reported in literature. Another

important part to be answered is in what extent the provided support will improve the condition of depressed persons since different supports or therapies will yield different responses and results during recovery from depression. It is essential to investigate the effectiveness of provided supports or therapies in order to select the best support or therapy for the patient. In this thesis, we study several therapies and supports strategies to be coupled with an ambient agent. We evaluate these strategies in term of global properties against evidences from the literature.

7 Research Approach

The research that is discussed in this thesis follows an ambient agent model development that considers the “natural science” like process as the means to advance scientific understanding. It is based on several grounding theories in psychology. However, theories used in psychology are often informal and making predications solely based on these theories are almost impossible. Therefore, a specific methodology is needed to overcome this dilemma.

7.1 Research Methodology

The methodology that has been used to explore human cognitive and physiological processes in depression and to apply of such models within ambient agent models encompasses a set of central elements. These central elements include:

- I. Identification of local dynamic properties.**
It is essential to capture the underlying mechanisms of the process under study (normally in informal representations) based on expert discussions, literature review or empirical evidence.
- II. Formalization of these local properties.**
In this phase, formal models are formulated on the basis of the underlying mechanisms obtained during the first phase. These formal models are intended to be in terms of executable dynamics properties to create executable models of the dynamic of the process. In this thesis, we used computational models to represent the dynamics of the models.
- III. Simulation.**
The formal models are then simulated in order to generate simulation traces. In addition, it provides an insight in the sequence of events over time in specific instances of the process. During this phase, we designed

and developed our simulated models using selected programming languages (C++, Visual.Net, Matlab) and tools (Leadsto, Temporal Trace Language).

IV. Identification of relevant non-local dynamic properties.

This phase aims to describe the process from an external observable perspective instead of its cognitive states. These non-local dynamic properties are expected to hold (or not to hold) for the process under investigation.

V. Formalization of these non-local dynamic properties.

These non-local properties are formalized in terms of global dynamic properties.

VI. Evaluation.

A set of local and global dynamic properties is verified against the generated simulation traces in step III. A verified model is an output from this phase.

This methodology has been applied for all chapters in this thesis.

7.2 Related Research Domains

The above research methodology involves many research domains that are relevant to the thesis research objectives. These domains are listed with some brief descriptions of how they contribute in this thesis.

I. Psychology.

It provides the underlying theories of depression, in several aspects from relapse and recurrent, cognitive vulnerability, and negative pattern information processing to emotional contagion within social networks. We used related theories as grounding references to develop computational models. In addition, this domain provides clinical theories and interventions for understanding, preventing, and alleviating depression. It aims to promote subjective well-being for the patients. Information from this domain allows us to design an intelligent support model that comprises important elements in cognitive therapies and social supports.

II. Computer Science.

Computer science provides a computational medium to formalize and verify the theoretical models of cognitive science and clinical psychology. Formal methods and computer simulations are a particular kind of

techniques used within this domain, especially for the specification, development, and verification of our models.

8 Research Scope

In this thesis, we investigate the dynamics of unipolar depression in terms of individual, care-giving interactions and social support networks through computational models. More specifically, we want to investigate the task of support or therapies for depressed people, and how it can be used in our models. For this purpose, important concepts and several underlying theories pertinent to the specific conditions are explored and used to develop related models. It is worth to mention that our models are restricted within the underlying theories existed in the psychological domain.

9 Thesis Outline

The thesis is based on a collection of articles. The majority of the chapters are reprints of refereed papers that have been published elsewhere, or extensions thereof. These articles are identical except for their layout. As a result, the overlap between the papers has not been removed, especially concerning the introduction and explanation of modelling approach. Furthermore, the articles can be read separately. All authors are cited in an alphabetical order and all can be regarded as having made a comparable contribution to the articles in the thesis, unless explicitly indicated otherwise.

9.1 Chapter Overview

This thesis consists of six parts, each focusing on a different aspect of ambient agent or computational models. Below, we outline each main part of the thesis.

I. Introduction.

In this part, we have motivated the development of computational models and ambient agent models, provided a provisional definition for them, and discussed several important elements that should be taken when developing them.

II. Computational Models for Individuals with a Risk of Unipolar Depression.

Part II presents three important computational models to describe the risk of depression. Chapter 2 introduces temporal dynamics in relapse and recurrence based on several pre-dispositions of internal and external factors, and Chapter 3 focuses on the dynamics in cognitive vulnerability, as a result from a series of defect beliefs about the negative feedbacks from the environment. Chapter 4 deals with the individuals cognitive coping skills, as a precursor to avoid future recurrence and relapse in depression. In summary, these three chapters provide the underlying frameworks to develop ambient agent models.

III. Ambient Agent Models to Support an Individual with a Risk of Unipolar Depression.

Several important concepts to design intelligent support models based on the integration with the computational models (from Part II) are covered in Part III. Chapter 5 explains the design of an ambient agent model to support relapse prevention. It encompassed a set of general supports and actions that can be delivered as a result of the analysis. Chapter 6 and Chapter 7 focus on specific therapies to reduce the risk of getting depressed associated with cognitive vulnerability and difficulties in coping skills.

IV. Computational Models for Depressed Individuals and Their Social Support Networks.

In this part, we present several dynamic models about exciting phenomena during depression among individuals within social support networks. In Chapter 8, we explain the dynamics of individual's tie preference when seeking for support during stress. The extension of this support seeking behaviour is covered in Chapter 9, where mutual support preference and receipts behaviour is modelled. Changing in perspective, Chapter 10 deals with the issues in the caregiving process, as an important concept to explain caregiving burnout, stress, and its relationship with the depressed individuals. Next, Chapter 11 presents interesting behaviours in emotion contagion and regulation processes within social support networks. Moreover, it shows how individuals can spread negative emotions or protect themselves from any negative consequence caused from this contagion process.

V. Ambient Agent Models to Support Depressed Individuals and their Social Support Networks.

Another important issue in caregiving and support provision process is to provide the right support for the depressed person while maintaining the well-being of the support providers and caregivers.

Part V consists of two chapters. First, in Chapter 12 we present an ambient agent model to automate support provider selection using a configuration approach in the patient's support network members that together will provide optimal support. Second, in Chapter 13 we present an ambient agent model that exploits model-based reasoning to assess the caregiver's state in order to generate dedicated actions that are tuned to the circumstances

VI. Discussion and Future Work.

In Part VI, we summarize our results, present future work for this thesis, and offer a set of challenges for building ambient agent systems in a real world environment.

9.2 Embedded Papers

This thesis is based on the following papers.

- Aziz, A.A., Klein, M.C.A., and Treur, J. (2009). An Agent Model of Temporal Dynamics in Relapse and Recurrence in Depression. In: Ali, M., Chen, S.M., Chien, B.C., Hong, T.P. (eds.), *Proceedings of the 22nd International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, (IEA-AIE 2009)*, Lecture Notes in Artificial Intelligence, Springer Verlag, pp. 36-45.
- Aziz, A.A., Klein, M.C.A., and Treur, J. (2009). An Agent Model for a Human's Social Support Network Tie Preference during Unipolar Depression. *The 9th IEEE/WIC/ACM International Conference on Intelligent Agent Technology (LAT 2009)*, In: Baeza-Yates, R. Lang, J. Mitra, S., Parsons, Pasi, G. (eds.), IEEE Computer Society Press, pp. 301-306.
- Aziz, A.A., Klein, M.C.A., and Treur, J. (2009). An Ambient Intelligent Agent for Relapse and Recurrence Monitoring in Unipolar Depression. In: C. Combi, Y. Shahr, A.A-Hanna. (eds.), *Proceedings of the 12th Conference on Artificial Intelligence in Medicine, (AIME 2009)*, Lecture Notes in Artificial Intelligence, Springer Verlag, pp. 186-190.
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- Aziz, A.A., and Treur, J. (2009). Modeling Dynamics of Social Support Networks for Mutual Support in Coping with Stress. In: Nguyen, N.T., Katarzyniak, R., Janiak, A. (eds.), *Challenges in Computational Collective Intelligence, Proceedings of the 1st International Conference on Computational Collective Intelligence, (ICCCI 09)*, Part B. Studies in Computational Intelligence, Springer Verlag, pp. 167-179.
- Aziz, A.A., Klein, M.C.A., and Treur, J. (2010). An Integrative Ambient Agent Model for Unipolar Depression Relapse Prevention. *Journal of Ambient Intelligence and Smart Environments, (JAISE 2010)*, IOS Press pp. 5-20.
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- Aziz, A.A., and Klein, M.C.A. (2010). Design of an Intelligent Support Agent Model for People with a Cognitive Vulnerability. In: Zhang, B., Wang, Y., Kinser, W. (eds.), *Proceedings of the 9th IEEE International Conference on Cognitive Informatics, (ICCI 2010)*, IEEE Computer Society Press, pp. 285-290.
- Aziz, A.A., Klein, M.C.A., and Treur, J. (2010). Simulating Cognitive Coping Strategies for Intelligent Support Agents. In: Catrambone, R., Ohlsson, S. (eds.), *Proceedings of the 32th Annual Conference of the Cognitive Science Society, (CogSci 2010)*, Cognitive Science Society, pp. 435-440.
- Aziz, A.A., and Klein, M.C.A. (2010). An Agent Based Simulation of the Dynamics in Cognitive Depressogenic Thought. *The 2nd International Conference on Agents and Artificial Intelligence (ICAART 2010)*, INSTICC Press, pp. 232-237.
- Aziz, A.A., Klein, M.C.A., and Treur, J. (2011). Intelligent Configuration of Social Support Networks around Depressed Persons. *Proceedings of the 13th Conference on Artificial Intelligence in Medicine, (AIME 2011)*, Lecture Notes in Artificial Intelligence, Springer Verlag, pp. 24-34.
- Azizi, A.A., Treur, J., and Wal, C.N. van der. (2011). An Agent-Based Model for Integrated Contagion and Regulation of Negative Mood. In: Kinny, D., Hsu, D. (eds), *Proceedings of the 14th International Conference on*

Principles and Practice of Multi-Agent Systems, (PRIMA 2011), Lecture Notes in Artificial Intelligence, Springer Verlag, (in press).

- Aziz, A.A., and Klein, M.C.A. (2011). Computational Modeling of Therapies Related to Cognitive Vulnerability and Coping. *2nd International Conference on Biologically Inspired Cognitive Architectures, (BICA 2011)*, IOS Press (in press).
- Aziz, A.A., and Klein, M.C.A. (2011). Incorporating an Ambient Agent to Support People with a Cognitive Vulnerability. Book Chapter in *Human-Computer Interaction: The Agency Perspective*, Springer Verlag, (in press).

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Part II

Computational Models for Persons with a Risk of Unipolar Depression

Chapter 2

An Agent Model of Temporal Dynamics in Relapse and Recurrence in Depression

This chapter appeared as:

Aziz, A.A., Klein, M.C.A., and Treur, J. (2009). An Agent Model of Temporal Dynamics in Relapse and Recurrence in Depression. In: Ali, M., Chen, S.M., Chien, B.C., Hong, T.P. (eds.), *Proceedings of the 22nd International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, (IEA-AIE 2009)*. Lecture Notes in Artificial Intelligence, Springer Verlag, pp. 36-45.

Furthermore, part of this chapter appeared as:

Aziz, A.A., Klein, M.C.A., and Treur, J. (2010). An Integrative Ambient Agent Model for Unipolar Depression Relapse Prevention. *Journal of Ambient Intelligence and Smart Environments (JAISE 2010)*, vol. 1(2), IOS Press, pp. 5-20.

“And the scariest part is that if you ask anyone in the throes of depression how he got there, to pin down the turning point, he’ll never know. There is the classic moment in *The Sun Also Rises* when someone ask Mike Campbell how he went bankrupt, and all he can say in response is, “Gradually and then suddenly.” When someone asks how I lost my mind, that is all I can say too.”

(Elizabeth Wurtzel, “Prozac Nation”)

An Agent Model of Temporal Dynamics in Relapse and Recurrence in Depression

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Abstract. This paper presents a dynamic agent model of recurrences of a depression for an individual. Based on several personal characteristics and a representation of events (i.e. life events or daily hassles) the agent model can simulate whether a human agent that recovered from a depression will fall into a relapse or recurrence. A number of well-known relations between events and the course of depression are summarized from the literature and it is shown that the model exhibits those patterns. In addition, the agent model has been mathematically analyzed to find out which stable situations exist. Finally, it is pointed out how this model can be used in depression therapy, supported by a software agent.

Keywords: agent based modeling, temporal dynamics, relapse and recurrent in depression.

1 Introduction

Unipolar depression is a mental disorder distinguished by a persistent low mood, and loss of awareness or contentment in usual activities [2]. Despite the modern era of pharmaceutical and holistic intervention, one of the primary problems with unipolar depression (i.e. a depression not related to other mental disorders) is that it has a very high rate of recurrent and relapse cases [14]. At least 60 percent of individuals who have had one depressive episode will have another, 70 percent of individuals who have had two depressive episodes will have a third, and 90 percent of individuals with three episodes will have a fourth episode [1]. Although the risk of relapse may decline with time, even for those who remain well for 5 years after an index episode, the rate of recurrence/relapse is 58 percent [3]. Despite the magnitude of the problem of recurrence and relapse, little attention has been focused on the symptom pattern in recurrent episodes of major depression [1][14]. In practice, there is a need to have a mechanism to monitor the condition of individuals who have had a previous encounter with unipolar depression, eventually improving their quality of life. In order to achieve this objective, the aim of the embedding research project is to develop an agent-based application that is able to support humans in the long term. The software agent is expected to have capabilities to understand its environment and the individual, providing a better monitoring and assessment of the situation. To implement this capability in any software agent, it is required to incorporate a human agent model that shows how humans might fall into relapse / recurrence or stay healthy. In case a relapse or recurrence is predicted, the agent can provide to support by providing adequate remedies.

This paper focuses exclusively on the formal model for dynamics in relapse/recurrence, as it is one of the essential components in the development of a software agent that is able to monitor individuals' conditions. In the next section, the underlying principles in relapse and recurrence in unipolar depression are discussed (Section 2). From this perspective, a formal model is designed and formulated (Section 3). Later, in Section 4, simulation traces are presented to illustrate how this model satisfies the expected outcomes in recurrent / relapse. In Section 5, a detailed mathematical analysis is performed, to identify equilibria in the model. Finally, Section 6 concludes the paper.

2 Underlying Principles of Relapse and Recurrence in Depression

Before presenting the model, the main characteristics of recurrence and relapse of depression as known from the literature are described. First, the effect of repeated stressful events is explained. Then, the knowledge about the causes of relapse and recurrence are discussed.

Frequent stressful events (stressors) are correlated with a positive contribution to the development of recurrence and relapse [3]. Contrary to popular belief, repeated strikes, even when they are low, can have almost the same effect as a similar single instantaneous stressful event [1][7]. This can be explained by an analogy of striking a bell. Imagine when a bell is struck once, it emits a sound that is loud at first, and then decays in intensity. However, if each subsequent strike is applied before the sound of the preceding strike has diminished: the loudness will increase each time. Applying this to the real world, a single and low stressor event may initially be so miniscule that it is considered to cause no effect. However, many repeated and small stressor events will eventually lead to a higher level of potential stress than a single major stress-producing event [3] [12]. Therefore, the intensity of a single stressor event faced by an individual is not the only important factor, because if negative events are persistently present, they can have a stronger effect than an initial event with a higher intensity.

A key step in the development of a model to represent potential onset of relapse and recurrence is to understand how this condition may recur [12]. Stressors from the environment are the dominant components that will lead to recurrence or relapse of depression [9]. This primary mechanism however is regulated by two main apparent predisposing factors, which influence the process as moderators that can neutralize each other. These two components are simplified as *immunity* and *neuroticism* (vulnerabilities in the personality) [3][5][6]. These factors are induced by the observed evidences that there are personal differences and conditions that will increase or decrease the onset of recurrence or relapse in any individual [9][11]. In addition, in many works, these two components are assumed to influence not only the possibility of onset of a depression, but also affect the duration of it [11][12]. On the other hand there are many factors that eventually help people to sustain their well-being. These factors are closely related to: (a) *coping skills*, (b) *being assertive*, and (c) *knowing when to seek help* [4][6][8]. The first is the ability to cope with the adversities. *Coping skill* is a behavioral and biologically wired tool which may be used by individuals to offset stressor events without correcting or eliminating the underlying condition. On the basis of many theories in depression, coping responses and strategies have been most frequently divided into problem focused coping and avoidant coping responses [9][10]. *Problem focus coping* responses allow an individual to increase the perceived control over their problem; it is proven in many studies that they are able to reduce the risk of onset of a depression [4]. They involve attempts to do something constructive about the stressful conditions that are harming an individual, rather than to make it worsen. In contrast, *avoidance coping* is detrimental in nature. When feelings of discomfort appear through stressor events, people find ways of not experiencing them. Such a strategy may work in a very short term, but it is mostly considered as an inadequate approach of coping [8]. The second component is being *assertive*. Individuals who are assertive tend to be aware of their emotions and communicate these in clear-cut manner and

are able to make and meet goals and challenges through respect and perseverance [5]. In many cases, people with a high assertive level are more likely to be more proactive and problem focused rather than unassertive individuals [1][9].

The last component is the ability to seek *social support*, (“having positive interaction of helpful behavior provided to a person in need of support”) [4]. As a multidimensional concept in nature, social support also includes many other facets that may finally determine if social support is constructed such as having the ability to create a support network [8][13]. There are many characteristics of individuals that influence their potential abilities of seeking support or vice versa. For example, an individual who is highly neurotic, using more avoidant coping and having a lack of self esteem may not be able to request support, and later it may disengage him/herself from potential social support.

In short, the following relations can be identified from the literature: (1) a series of smaller stressor events can lead to the recurrence or relapse; (2) stressor events directly affect the potential onset of relapse/recurrence; (3) neuroticism aggravates the effect of stressor events on the potential onset of a depression; (4) assertiveness and immunity will diminish the potential of onset, and (5) a combination of good social support and coping skills will reduce the risk of having future relapse/recurrence.

3 Model for Relapse and Recurrence

The characteristics of the proposed model are heavily inspired by the research discussed in the previous section on recurrence and relapse, especially in depression. In particular, this model combines ideas from research in affective disorder, prevention medicine, artificial intelligence, and dynamic modeling. Those ideas are encapsulated in a way that allows to simulate how an individual is fragile towards stressors, and possibly further develops a depression. All of these concepts (and their interactions) are discussed in the following paragraphs in this section.

3.1 Formalizing the Model Relationships

In this model, there are four major components that will represent dynamic interactions of human agent abilities involved in recurrence/relapse namely; *environment*, *personality*, *social support*, and *coping strategies*. By combining these characteristics together, it will allow a hypothesis or expected behavior for the human agent to be monitored.

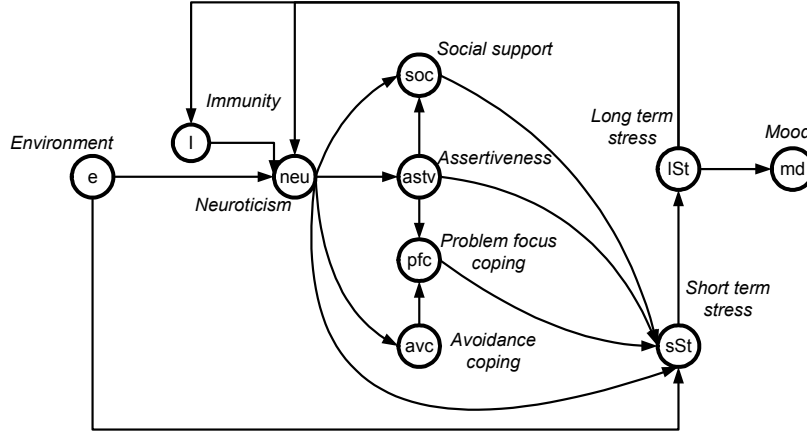


Fig. 1. Global Relationships of Variables Involved in the Onset of Relapse and Recurrence Depression.

Once the structural relationships in the model have been determined, the model can be formalized. In the formalization, all nodes are designed in a way to have values ranging from 0 (low) to 1 (high). The interaction will determine the new value of it, either by a series of accumulations or an instantaneous interaction for each node.

Stressor Events: In the model, the stressor events (e) are generated by simulating potential effects throughout t time using weighted sum of three types of events; life (le), chronic (ce), and daily (de) events.

$$e(t) = w_1.le(t) + w_2.ce(t) + w_3.de(t) \quad (1)$$

The role of these factors in the model is to represent a series of events. Stressors are seen as very intense when $e(t) \rightarrow 1$, and no stressors are represented by $e(t) \rightarrow 0$.

Dynamics of Neuroticism: In this model, the neurotic level (neu) describes the interactions between environment (e), personal immunity trait (I), and prior exposure to long-term stress (lSt), in a time interval between t and $t+\Delta t$. Here, α_{neu} is a parameter for a change rate, and β_{neu} is a parameter for the contribution effect of the previous neurotic rate in this equation.

$$neu(t+\Delta t) = neu(t) + \alpha_{neu} \cdot (1 - neu(t)) \cdot [f(e(t), I(t)) \cdot lSt(t) - \beta_{neu} \cdot neu(t)] \cdot \Delta t \quad (2)$$

where, $f(e(t), I(t))$ is a logistic unit function, $1 / (1 + \eta e^{\alpha(e(t)-I(t))})$

Social Support, Problem Focus Coping, Assertiveness, and Immunity:

Social support (*soc*) is computed by multiplying the factor of being assertive by the ability of less or non-neurotic. Problem focus coping (*pfic*) is also computed with the same approach, but with a negative association in avoidant coping (*avc*). The α_{avc} is a proportional rate for the effect of neurotic level in *avc*.

$$soc(t) = astv(t) \cdot (1 - neu(t)) \quad (3)$$

$$pfic(t) = astv(t) \cdot (1 - avc(t)) \quad (4)$$

$$avc(t) = \alpha_{avc} \cdot neu(t) \quad (5)$$

Assertiveness (*astv*) depends on the interaction between the normal assertive value within an individual and the condition of being less or non-neurotic. The immunity (*I*) level interaction also having a similar behavior, but it is related to the interaction in a long term stress level.

$$astv(t) = \alpha_{astv} \cdot astv_{norm} + (1 - \alpha_{astv}) \cdot (1 - neu(t)) \cdot astv_{norm} \quad (6)$$

$$I(t) = \alpha_I \cdot I_{norm} + (1 - \alpha_I) \cdot (1 - lSt(t)) \cdot I_{norm} \quad (7)$$

Dynamics of Short Term Stress, Long Term Stress, and Mood: Short term stress (*sSt*) is modeled by instantaneous relationships between the environment, neurotic level, and reducer components, ψ (a combination of social support, assertiveness, and problem focus coping). Long term stress (*lSt*) is primarily contributed the accumulation exposure towards short term stress and later will influence the level of mood (*md*) in a time interval between t and $t + \Delta t$.

$$sSt(t) = \beta_{sSt} \cdot e(t) + (1 - \beta_{sSt}) \cdot neu(t) \cdot (1 - e(t)) \cdot (1 - \psi) \quad (8)$$

$$lSt(t + \Delta t) = lSt(t) + \alpha_{lSt} \cdot (1 - lSt(t)) \cdot (sSt(t) - \beta_{lSt} \cdot lSt(t)) \cdot \Delta t \quad (9)$$

$$md(t + \Delta t) = md(t) + \eta_{md} \cdot (1 - md(t)) \cdot (lSt(t) - \beta_{md} \cdot md(t)) \cdot \Delta t \quad (10)$$

where η_{md} , β_{md} , α_{lSt} , β_{sSt} and β_{lSt} denote the proportion change rates for all respective equations.

4 Example Simulation Traces

In this section, the model was executed to simulate a large number of conditions of individuals. In this section, three examples are shown: a healthy individual (**A**), an individual with a potential risk of relapse and recurrence (**B**), and an individual with severe conditions (**C**). The initial settings for the different individuals are the following ($neu(t=0)$, $astv_{norm}$, I_{norm}); **A** (0.1, 0.8, 0.8), **B** (0.5, 0.5, 0.4), and **C** (0.8, 0.2, 0.1). In all cases, the initial long term stress and mood value is initialized as 0.3, 0.1 respectively. Corresponding to these settings, the level of

severity (or potential onset) is measured, defining that any individuals scored more than 0.5 in their mood level (within more than 336 time steps) will be considered as reaching the recurrent or relapse stage. These simulations used the following parameters settings: $t_{max}=1000$ (to represent a monitoring activity up to 42 days), $\Delta t=0.3$, $\alpha_{st}=0.3$, $\eta_{md}=0.2$, $\beta_{st}=0.3$, $\alpha_t=0.7$, $\alpha_{astv}=0.5$, $\alpha_{ave}=0.5$, $\alpha_{neu}=0.4$, and with all decay terms are assigned as 0.02.

Result # 1: Simulation Trace for Prolonged-Fluctuating Stressor Events

During this simulation, each type of individual has been exposed to an extreme stream of stressor events, with a rapid alteration between each corresponding event. This kind of pattern is comparable to the repeated strike event, where stressor events always occur when the previous events were ended.

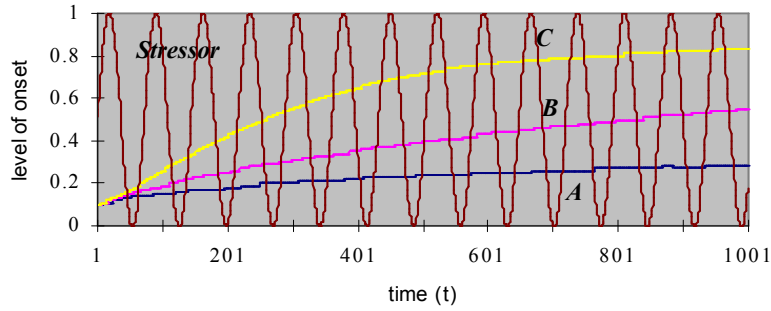


Fig.2. Relapse/Recurrent Onset for Each Individual in Prolonged Stressor Events.

In this simulation trace, it shown that an individual C(*high neurotic, low in assertive and immunity*) tends to get into onset much faster compared to other individuals. Note that the individual B(*moderate neurotic, assertive, and immunity*) shows a gradual increasing level of potential onset and possibly will experience relapse/recurrent if that individual is having constant exposure towards stressors. Individual A however is less prone to develop a potential onset condition within a short period of time.

Result # 2: Simulation Trace for Decrease Stressor Events

This simulation trace shows two types of periods, one with a very high constant and with a very low constant stressor event. These events occurred in a constant behavior for a certain period of time (approximately within 20 days).

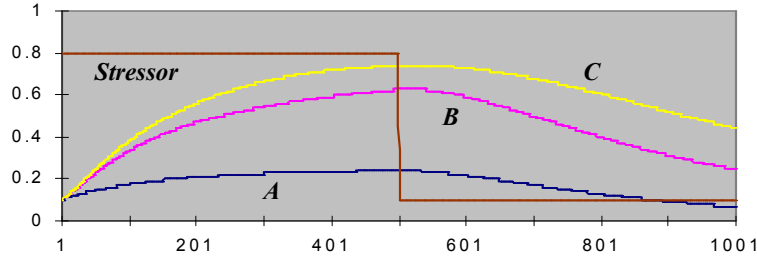


Fig.3. Relapse / Recurrent Onset for Each Individual in Fluctuated Stressor Events.

Also here it can be seen that individual C gets into a bad mood much faster than the others. Moreover, even at the end of the simulation time, the mood of individual C is worse than the mood of the other two individuals. Using a similar experimental setting, with $t_{\max}=10,000$, the end of the experimental results show all individuals will have a normal mood level.

Result # 3: Simulation Trace with Social Support, and Problem Focus Coping Skills (Reducer)

As initially discussed in Section 2, a combination of social support, and problem focus coping skills is expected to help any individuals to reduce potentially risk in relapse / recurrence. The combination of these factors will be represented by R_A , R_B , and R_C for the respective human agents. To visualize the effect of these, frequently repeating low stressor events were simulated. Figure 4 illustrates how these combinations, mood levels and stressor events are influencing each other.

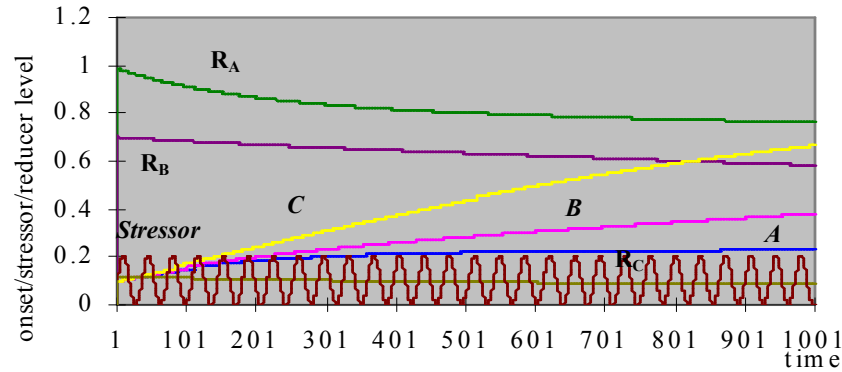


Fig.4. Relapse / Recurrent Onset for Each Individual With a Combination of Reducer.

Figure 4 shows that a healthy individual (4) has much higher reducer factors than less healthy individuals. These reducing factors limit the effect of the incoming stressors. Also it can be seen that the reducer factors decrease over time, due to the relatively low but frequent stressors. The patterns for the different individuals are the same as in Figure 2, although the final mood level is lower in Figure 4 because of the less intense stressors fluctuation.

To wrap up these experimental results, the simulation traces described above satisfactorily explain the relations as summarized in Section 2. In all simulation traces, it is shown that individuals with higher assertiveness, immunity and less neurotic levels develop less often a relapse compared those who are not. In addition, a higher neurotic level eventually aggravates the potential risk of onset, as illustrated in all simulation traces. The effects of stressor events on relapse/recurrence onset are also exemplified. In all simulation traces, it is apparent that frequent or high stressor events contribute to the potential risk of onset. Furthermore, the effect of the reducers is also examined, where in Figure 4, it depicts that when the reducer level is decreasing, the person is also prone to a relapse, or vice versa. This distillation of above evidences and traces illustrates that this model reflects the basic relations that are known to influence relapse and recurrence, given certain criteria of events and personality attributes.

5 Mathematical Analysis

In this section the equilibria are analyzed that may occur under certain conditions. The equilibria describe situations in which a stable situation has been reached. Those equilibria are interesting as it should be possible to explain them using the knowledge of the domain that is modeled. As such, the existence of reasonable equilibria is an indication for the correctness of the model. To analyze the equilibria, the available temporal and instantaneous equations are filled with values for the model variables such that the derivatives or differences between time point t and $t + \Delta t$ are all 0 (in particular for neuroticism, long term stress and mood). Moreover, for an equilibrium, the external input is also assumed to be constant. To start, for an equilibrium for neuroticism it holds as;

$$(1 - neu) \cdot (f(e, I) \cdot lSt - \beta_{neu} \cdot neu) = 0$$

This is equivalent to $neu = 1$ or $neu = f(e, I) \cdot lSt / \beta_{neu}$, where $f(e, I) = 1 / (1 + \eta e^{\alpha(e-I)})$. Assuming high steepness of the threshold function provides the cases $e \leq I$ (where $f(e, I) = 0$) or $e > I$ (where $f(e, I) = 1$). Under this assumption the cases are $neu = 1$ or $neu = 0$ and $e \leq I$ or $neu = lSt / \beta_{neu}$ and $e > I$. For an equilibrium for assertiveness it holds;

$$\begin{aligned} astv &= \alpha_{astv} \cdot astv_{norm} + (1 - \alpha_{astv}) \cdot (1 - neu) \cdot astv_{norm} \\ &= astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm} \end{aligned}$$

Meanwhile, for an equilibrium for immunity it holds:

$$I = \alpha_1 I_{norm} + (1 - \alpha_1) (1 - lSt). \quad I_{norm} = I_{norm} - (1 - \alpha_1) lSt I_{norm}$$

For an equilibrium for long term stress it holds $(1 - lSt) (sSt - \beta_{lst} lSt) = 0$, which is equivalent to $lSt = 1$ or $sSt = \beta_{lst} lSt$. For an equilibrium for mood it holds $(1 - md) (lSt - \beta_{md} md) = 0$ which is equivalent to $md = 1$ or $md = lSt / \beta_{md}$. Table 1 provides a summarization of these equilibria.

Table 1. Equilibrium Equations for Respective Variables.

Var.	Equilibrium equations
neu	$neu = 1$ or $e \leq I$ and $neu = 0$ or $e > I$ and $\beta_{neu} neu = lSt$
$astv$	$astv = astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm}$
soc	$soc = astv \cdot (1 - neu) = (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm}) (1 - neu)$
avc	$avc = \alpha_{avc} neu$
$pf\bar{c}$	$pf\bar{c} = astv \cdot (1 - avc) = (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm}) (1 - \alpha_{avc} neu)$
I	$I = I_{norm} - (1 - \alpha_1) lSt. \quad I_{norm} = I_{norm} - (1 - \alpha_1) lSt I_{norm}$
sSt	$sSt = \beta_{sst} e + (1 - \beta_{sst}) \cdot neu \cdot (1 - e) \cdot (1 - \psi)$ $where \quad \psi = w_1 \cdot soc + w_2 \cdot pf\bar{c} + w_3 \cdot astv$ $= \beta_{sst} e + (1 - \beta_{sst}) \cdot neu \cdot (1 - e) \cdot (1 - (w_1 \cdot (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm}) (1 - neu)) + w_2 (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm}) (1 - \alpha_{avc} neu)) + w_3 \cdot (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm})))$
lSt	$lSt = 1$ or $sSt = \beta_{lst} lSt$
md	$md = 1$ or $md = lSt / \beta_{md}$

It turns out that all values can be expressed in terms of either neu or lSt : in the Table 1 the values $astv$, soc , avc , $pf\bar{c}$ have been expressed in neu , and the values md , sSt , I have been expressed in lSt . Then by the equation for short term stress the value lSt can be expressed in neu .

$$\beta_{lst} lSt = \beta_{sst} e + (1 - \beta_{sst}) \cdot neu \cdot (1 - e) \cdot (1 - (w_1 \cdot (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm}) (1 - neu)) + w_2 (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm}) (1 - \alpha_{avc} neu)) + w_3 \cdot (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm})))$$

From the equation for neuroticism two cases occur; $e \leq I$ and $neu = 0$ or $e > I$ and $\beta_{neu} neu = lSt$. These cases will be addressed in some more detail.

Analysis of Case $e \leq I$ and $neu = 0$

In this case, the following values are found:

$$\begin{aligned} neu &= 0, \quad astv = astv_{norm}, \quad soc = astv_{norm}, \quad avc = 0, \quad pf\bar{c} = astv_{norm} \\ sSt &= \beta_{sst} e, \quad lSt = \beta_{sst} e / \beta_{lst}, \quad I = I_{norm} - (1 - \alpha_1) \cdot \beta_{sst} e / \beta_{lst} \cdot I_{norm} \\ md &= 1 \quad \text{or} \quad md = \beta_{sst} e / \beta_{lst} \beta_{md} \end{aligned}$$

Here the condition $e \leq I$ is equivalent to: (1) $e \leq I_{norm} - (1 - \alpha_t) \cdot \beta_{sst} \cdot e / \beta_{lst} \cdot I_{norm}$, (2) $e (1 + (1 - \alpha_t) \cdot \beta_{sst} / \beta_{lst} \cdot I_{norm}) \leq I_{norm}$, and (3) $e \leq I_{norm} / (1 + (1 - \alpha_t) \cdot \beta_{sst} / \beta_{lst} \cdot I_{norm})$. These conditions illustrate the generic condition that an extremely healthy individual (not neurotic at all) that encounters only events that are less intense than its immunity level will never develop a relapse.

Analysis of Case $e > I$ and $\beta_{neu} neu = ISt$:

In this case the equation becomes:

$$\beta_{lst} \beta_{neu} neu = \beta_{sst} e + (1 - \beta_{sst}) \cdot neu \cdot (1 - e) \cdot (1 - (w_1 \cdot (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm}) (1 - neu)) + w_2 (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm}) (1 - \alpha_{avc} neu)) + w_3 (astv_{norm} - (1 - \alpha_{astv}) \cdot neu \cdot astv_{norm})))$$

Rewriting this equation in general, provides an equation of third degree, which for given values of the parameters can be solved in an algebraic manner or numerically. For some special cases of parameter values the equation becomes simpler. For example, when $\alpha_{astv} = 1$, it becomes a quadratic equation:

$$\beta_{lst} \beta_{neu} neu = \beta_{sst} e + (1 - \beta_{sst}) \cdot neu \cdot (1 - e) \cdot (1 - (w_1 \cdot astv_{norm} (1 - neu) + w_2 \cdot astv_{norm} (1 - \alpha_{avc} neu)) + w_3 \cdot astv_{norm} neu \cdot astv_{norm})))$$

This situation describes how an individual that encounters events which are more intense than its immunity level will not change, if his long-term stress level is in balance with his level of neurotiscm.

6 Conclusion

The grand challenge addressed in the research that is reported in this paper is to develop a software agent that is capable of monitoring individuals' condition in certain events. In this paper a first step has been taken. A model has been developed that is able to explain the onset of recurrence and relapse based on personal characteristics and stressor events. The proposed model is heavily inspired by scientific findings about the relapse or recurrence onset. Having this foundation, a formal model has been developed and used to simulate different individuals' situations, which corresponded to their personality and characteristics. A mathematical analysis has been performed to demonstrate the occurrence of equilibrium conditions, fundamentally beneficial to describe convergence and stable state of the model. The proposed model provides a basic building block in designing a software agent that will support the human. Future work of this agent and model integration will be specifically focus how interactions and sensing properties can be further developed and enriched, to promote a better way to fluidly embedded this into any monitoring and health informatics system.

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Chapter 3

An Agent Based Simulation of the Dynamics in Cognitive Depressogenic Thought

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“Nightingales are put in cages because their songs give pleasure. Whoever heard of keeping a crow?”

(Jalal ad-Din M Rumi, “The Essential Rumi”)

An Agent Based Simulation of the Dynamics in Cognitive Depressogenic Thought

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Abstract: Depression is a common mental disorder. Appropriate support from others can reduce the cognitive distortion that can be caused by subsequent depressions. To increase our understanding of this process, an agent model is presented in this paper in which the positive and negative effects of social support and its relation with cognitive thoughts are modelled. Simulations show the effect of social support on different personality types. A mathematical analysis of the stable situations in the model gives an additional explanation of extreme cases. Finally, a formal verification of expected relations between support, risk factors and depressive thoughts is performed on the simulation traces to check whether the simulations describe realistic processes.

Keywords: agent based simulation, affective disorder, cognitive depressogenic formation, social support feedbacks.

1 Introduction

Cognitive vulnerability is one of the main concepts that play an important role to escalate the risk of relapse in affective disorder (depression). In a broader spectrum, it is a defect belief, or structures that are persistently related for later emergent in psychological problems. Before further reviewing the underlying concepts of the vulnerability, it is essential to understand its connection between relapse condition in unipolar depression and social support [3]. Unipolar depression is a mental disorder, distinguished by a persistent low mood and loss of awareness in usual activities [4]. Normally, under a certain degree of stressors exposure, an individual with a history of depression will develop a negative cognitive content (thought), associated with the past losses. Such cognitive content is often related to the maladaptive schemas, which in a long run will cause individual's ongoing thought capability to be distorted and later to be dysfunctional [12].

However, this cognitive distortion can be reduced through appropriate supports from other members within the social support network [10]. Social support network is made up of friends, family and peers. Some of it might be professionals and support individuals in very specific ways, or other people in this network might be acquaintances in contact with every day. It has been suggested that social support naturally can help to prevent and decrease stress through positive inferences, which later curbs the formation of cognitive vulnerability [2]. However, some literatures have shown that certain supports provide contrast effects. Rather than attenuating the negative effects from stressors, it will eventually amplify the individual's condition to get worse [7].

In this paper, these positive and negative effects from social support interaction and its relation with cognitive thought are explored. To fulfil this requirement, a dynamic model about cognitive depressogenic thought is proposed. The proposed model can be used to approximate a human's cognitive depressogenic thought progression throughout time. This paper is organized as follows. The first section introduces main concepts and existing theory of cognitive depressogenic thought and hopelessness. Thereafter, a formal model is described and simulated (Section 3 and 4). The model has been verified by a mathematical analysis (Section 5) and by checking properties of simulation traces (Section 6). Finally, Section 7 summarizes the paper with a discussion and future work for this model.

2 Fundamentals in Cognitive Depressogenic Thought

People vary in their abilities to overcome stressful life events and it allows them to manage their troubles and not be overwhelmed. These variations answer why the level of severity and duration among different individuals can be diverse in nature. To explain this mechanism, the Extended Hopelessness Theory of Depression is used. In this theory, people who exhibit a negative inferential style, in which they describe, attribute negative events to stable (likely to persist over time) and global (likely to affect many aspects of life) will most likely to infer themselves as fundamentally useless and flawed [1]. Although it is well documented that social support mitigates a risk of relapse, but there is a condition where feedbacks from the social support members may indirectly escalate the risk of relapse. Such feedbacks are considered as “maladaptive inferential feedback” (MIF), and normally increase the negative thought formation [2]. Contrary to this, an adaptive inferential feedback (AIF) provides a buffer to reduce the threat, by countering negative inferences for negative event. AIF asserts that when a social support member offers comfort by attributing the source of negative event to be unstable, it will later diminish the risk of creating maladaptive inferences [9].

In addition, the Extended Hopelessness Theory of Depression relates the development cognitive depressogenic thought through previously described two precursors. First, the present of positive social support feedback (AIF) acts as a buffer to decrease individuals’ possibility of having cognitive depressogenic thought over time. Second, individuals with cognitive depressogenic thought will make negative inferences when facing negative events. This condition is also associated with less AIF from the social support members. Moreover, both of these conditions capable to predict changes in stressful events. Therefore, it can be further used to elaborate the immunity level of individuals (as contrast in vulnerability concept). In addition, many studies have also associated the lower risk of depression with the presence of AIF [7]. As indicated in several previous works, inferential feedbacks provide one of the substantial factors towards the development of cognitive depressogenic thought over time. By combining either one of these two factors together with situational cues, it leads to the formation of either cognitive depressogenic inference or positive attributional style. Situational cues refers to a concept that explains individuals’ perception that highly influenced by cues from events (environment). Individuals under the influence of negative thought about themselves will tend to reflect these negative cognitions in response to the occurrence of stressors. These later develop the conditions called “stress-reactive rumination” and “maladaptive inference” [13].

Stress reactive rumination reflects a condition where individuals have difficulty in accessing positive information, and further develop a negative bias towards inference (maladaptive inference). This process is amplified by previous exposures towards cognitive depressogenic thought episode. After a certain

period, both conditions are related to the formation of hopelessness. Hopelessness is defined by the expectation that desired outcome will not occur, or there is nothing one can do to make it right [11]. Prolong and previous exposure from hopelessness will lead to the development of cognitive depressogenic thought. However, this condition can be reduced by having a positive attributional style, which normally existed during the presence of AIF and low situational cues perception [8].

In short, the following relations can be identified from the literature: (1) prolong exposure towards MIF, negative events, and high-situational cues can lead to the development of cognitive depressogenic thought. (2) a proper support (AIF) will reduce the risk of further development of future cognitive depressogenic thought. (3) Individuals with high situational cues and proper support will be less effective in reducing the progression of cognitive depressogenic thought, compared to the individuals with less situational cues.

3 A Dynamical Domain Model of Cognitive Depressogenic Thought

This section discusses the details of the dynamic model. In this domain model, three major components namely; environment, inferential feedbacks, and thought formation will represent the dynamic of interactions between social support feedback and individuals involved in negative thought formation during the beginning of relapse and recurrence in depression. In the formalization, those important concepts are translated into several interconnected nodes. These nodes are designed in a way to have values ranging from 0 (low) to 1 (high). Figure 1 depicts the global interaction between these nodes. The interaction will determine the new value of it, either by a series of accumulations or an instantaneous interaction for each node.

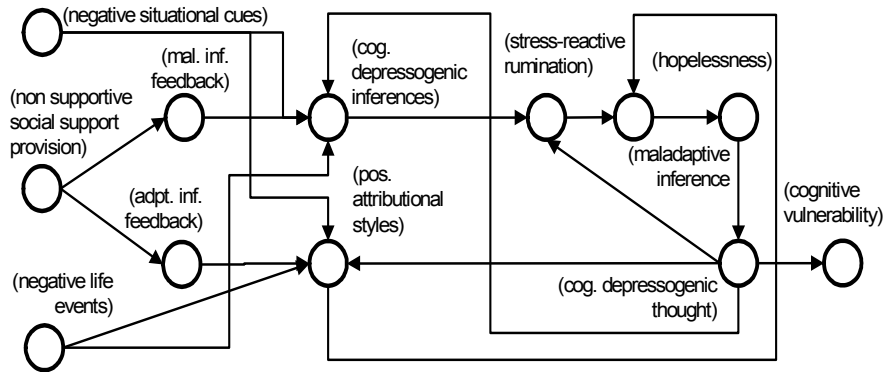


Fig. 1. Overview of the Domain Model in Cognitive Vulnerability.

3.1 Ontology

To formalize the concepts of properties on dynamics relationship introduced in the previous section (Section 2), for each of them, a logical atom using predicate calculus is introduced; see Table 1. Note that all atoms make use of sorts. The specific sorts that are used in the presented model are AGENT, which represents an agent, and REAL, stands for the set of real numbers. To formalize the dynamic relationship between these concepts (as depicted in Figure 1), the following temporal relationships are used.

Table 1: Formalization of Concepts Used for Model.

Concepts	Formalization
Life events	life_event(X:AGENT, R:REAL)
Chronic events	chronic_event(X:AGENT, R:REAL)
Daily events	daily_event(X:AGENT, R:REAL)
Negative events	neg_event(X:AGENT, R:REAL)
Situational cues	sit_cues(X:AGENT, R:REAL)
Adaptive inferential feedback	adapt_inf(X:AGENT, R:REAL)
Maladaptive inferential feedback	maladap_fb(X:AGENT, R:REAL)
Cognitive depressogenic inferences	cog_dep_inf(X:AGENT, R:REAL)
Positive attributional style	pos_att_style(X:AGENT, R:REAL)
Stress reactive rumination	sts_reactive(X:AGENT, R:REAL)
Maladaptive inference	maladap_inf(X:AGENT, R:REAL)
Hopelessness	hoplness(X:AGENT, R:REAL)
Cognitive depressogenic thought	cog_dep_tgt(X:AGENT, R:REAL)
Cognitive vulnerability	cog_vulnerability(X:AGENT, R:REAL)

3.2 Temporal Specification

In order to develop a model, a temporal specification language called LEADSTO and its supporting software environment has been used. LEADSTO enables one to model direct temporal relationship between two state properties (dynamic properties) [6]. Consider the format of $\alpha \rightarrow_{e,f,g,h} \beta$, where α and β are state properties in form of a conjunction of atoms (conjunction of literals) or negations of atoms, and e,f,g,h represents non-negative real numbers. This format can be interpreted as follows;

If state α holds for a certain time interval with duration g , after some delay (between e and f), state property β will hold a certain time interval of length h .

Here, atomic state properties can have a qualitative, logical format to represent certain observed conditions. In addition, this representation also holds a temporal trace denoted by $\gamma \models \alpha \xrightarrow{e,f,g,h} \beta$, if

$$\begin{aligned} & \forall t1[\forall t1[t1 - g \leq t < t1 \Rightarrow \alpha \text{ holds in } \gamma \text{ at time } t] \\ & \Rightarrow \exists d [e \leq d \leq f \ \& \ \forall t' [t1 + d \leq t' < t1 + d + h] \Rightarrow \beta \text{ holds in } \gamma \text{ at} \\ & \text{time } t']] \end{aligned}$$

For a more detailed discussion of this language, see [5]. To formalize the concepts of properties on dynamics relationship introduced in the previous section (Section 2), for each of them, a logical atom using predicate calculus is introduced. The following temporal relationships are used to formalize the dynamic relationship between those concepts.

NEVT: Negative events

A set of generated events is experienced by an agent X through simulation of several conditions using weighted sum of life L , chronic C , and daily D events, where w_1, w_2, w_3 are weights for L, C , and D respectively with $\sum w_i = 1$.

$\forall X: \text{AGENT}$

$$\text{life_event}(X, L) \wedge \text{chronic_event}(X, C) \wedge \text{daily_event}(X, D) \xrightarrow{} \text{neg_event}(X, w_1.L + w_2.C + w_3.D)$$

PTS: Positive attributional style

If the agent X faces bad situational cues B , negative events Ne , cognitive depressogenic thought Cd , adaptive inferential style AiF , and has a proportional contribution towards positive attributional style indicated by parameter η then the positive attributional style level is $\eta.AiF + (1-\eta).(1-(B.Ne.Cd)).AiF$.

$\forall X: \text{AGENT}$

$$\begin{aligned} & \text{sit_cues}(X, B) \wedge \text{neg_event}(X, Ne) \wedge \text{adapt_inf}(X, AiF) \wedge \text{cog_dep_tgt}(X, Cd) \\ & \xrightarrow{} \text{pos_att_style}(X, \eta.AiF + (1-\eta).(1-(B.Ne.Cd)).AiF) \end{aligned}$$

CDI: Cognitive depressogenic inferences

If the agent X experiences the intensity levels of experiences negative inferential style MiF , situational cues B , cognitive depressogenic thought Cd , negative events Ne and has a proportional contribution towards inferences indicated by parameter α then the cognitive depressogenic inferences level is $\alpha.MiF + (1-\alpha).(B.Ne.Cd).MiF$.

$\forall X: \text{AGENT}$

$$\begin{aligned} & \text{sit_cues}(X, B) \wedge \text{neg_event}(X, Ne) \wedge \text{maladapt_fb}(X, MiF) \wedge \text{cog_dep_tgt}(X, \\ & Cd) \xrightarrow{} \text{cog_dep_inf}(X, \alpha.MiF + (1-\alpha).(B.Ne.Cd).MiF) \end{aligned}$$

STR: Stress reactive rumination

If the agent X experiences the intensity levels of cognitive depressogenic thought Cd , and cognitive depressogenic inference CDi and has a proportional regulator indicated by parameter β then the stress reactive rumination level is $\beta.CDi + (1-\beta).Cd$.

$\forall X:AGENT$

$cog_dep_inf(X, CDi) \wedge cog_dep_tgt(X, Cd) \rightarrow$
 $sts_reactive(X, \beta.CDi + (1-\beta).Cd)$

MDI: Maladaptive inference

If the agent X faces stress reactive rumination in SR level and perceives positive attributional style PS level and has a proportional contribution regulator indicated by parameter γ then the maladaptive inference level is $\gamma.SR.(1-PS)$.

$\forall X:AGENT$

$sts_reactive(X, SR) \wedge cog_pos_att_style(X, PS) \rightarrow$
 $maladap_inf(X, \gamma.SR.(1-PS))$

CV: Cognitive vulnerability

If the agent X experiences the intensity levels of cognitive depressogenic thought Cd , and has previous level of cognitive vulnerability Cv and has an adaptation rate indicated by parameter λ then the cognitive vulnerability for agent X after Δt is $(Cv + \lambda.(1-Cv).(Cd-Cv).Cv.\Delta t)$.

$\forall X:AGENT$

$cog_dep_tgt(X, Cd) \wedge cog_vulnerability(X, Cv) \rightarrow cog_vulnerability(X, Cv +$
 $\lambda.(1-Cv).(Cd-Cv).Cv.\Delta t)$

HPS: Hopelessness

If the agent X faces level of maladaptive inference MDi and has previous level of hopelessness Hp and has adaptation rate indicated by parameter ψ then the hopelessness level for agent X after Δt is $Hp + (1-Hp).\psi.(MDi-Hp).Hp.\Delta t$

$\forall X:AGENT$

$maladap_inf(X, MDi) \wedge hoplness(X, Hp) \rightarrow hoplness(X, (1-Hp).\psi.(MDi-$
 $Hp).Hp.\Delta t)$

CD: Cognitive depressogenic thought

If the agent X faces level of hopelessness Hp and has previous level of cognitive depressogenic thought Cd and has an adaptation rate indicated by parameter ϕ then the cognitive depressogenic thought level for agent X after Δt is $Cd + (1-Cd).\phi.(Hp-Cd).Cd.\Delta t$.

$\forall X:AGENT$

$$\text{hoplness}(X, \text{Hp}) \wedge \text{cog_dep_tgt}(X, \text{Cd}) \rightarrow \text{cog_dep_tgt}(X, \text{Cd} + (1 - \text{Cd}) \cdot \phi(\text{Hp} - \text{Cd}) \cdot \text{Cd} \cdot \Delta t)$$

4 Simulation Results

In this section, the model was executed to simulate several conditions of agents with the respect of exposure towards negative events, feedbacks from the social support members, and situational cues. With variation of these conditions, some interesting patterns can be obtained, as previously defined in the earlier section. For simplicity, this article shows several cases of cognitive depressogenic thought levels formation using three different agent attributes. These cases are; (i) an agent **Heidi** with a good feedback from the social support members, and using a good judgment about the situation ($B=0.2$, $MiF=0.1$, $AiF=0.8$), (ii) an agent **Kees** that receives good feedbacks but with bad judgment about the situation ($B=0.8$, $MiF=0.1$, $AiF=0.9$), and (iii) an agent **Piet** with bad feedbacks from the social support, and bad judgment about the situation ($B=0.9$, $MiF=0.8$, $AiF=0.1$). The duration of the simulated scenario is up to $t = 1000$ (to represent the conditions within 42 days) with three negative events. The first event consisted of the prolonged and gradually decreased stressors, the second event dealt with the decreased stressor, while the third event simulated repeated stressors. For all conditions, the initial cognitive depressogenic thought was initialized as 0.5.

Case #1: Prolonged Repeated Stressor with Different Individuals Inferential Feedback and Situation Cues

During this simulation, each type of individual attribute has been exposed to a prolonged stressor condition. The result of this simulation is shown in Figure 2.

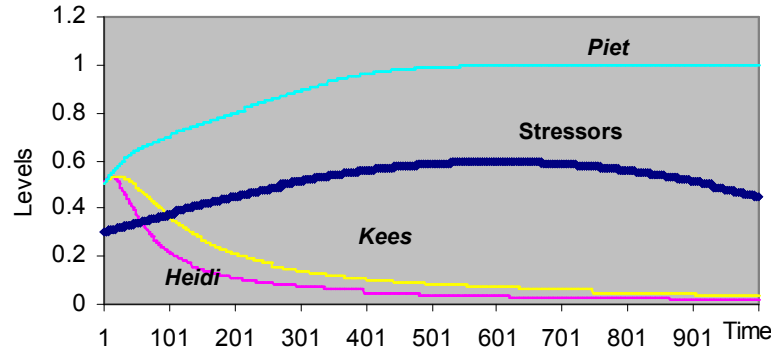


Fig. 2. Cognitive Depressogenic Level for Each Individual during Prolonged Stress Events.

In this simulation trace, it shown that *Piet* (*high situational cues*, and *negative inferential feedback*) tends to develop a cognitive depressogenic thought, in contrast with the others. *Heidi* (*low situational cues*, and *positive inferential feedback*) shows a rapid declining pattern in developing the cognitive condition. Note that *Kees* (*high situational cues* and *positive inferential feedback*) has also developed a decreasing pattern towards the cognitive condition. However, *Kees* has a lesser decreasing effect towards a negative thought despite a high positive support, given that this individual tends to perceive negative view about the situation. Persistent positive support from the social support members helps each agent to reduce the development of cognitive thought throughout time.

Case #2: Decreased Stressor with Different Individual Inferential Feedback and Situational Cues

In this simulation trace, there are two conditions were introduced, one with a very high constant stressor, and with no stressor event. These events simulate the condition of where agents were facing a sudden change in their life, and how inferential feedbacks and perceptions towards events play important to role towards the diminishing of cognitive thought. The result of this simulation is shown in Figure 3.

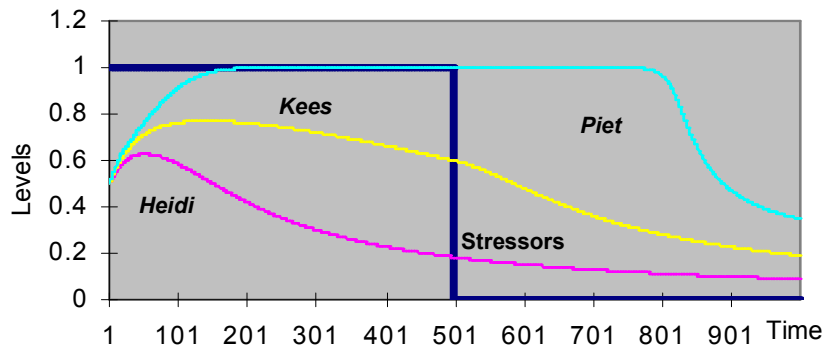


Fig. 3. Cognitive Depressogenic Level for Each Individual during Fluctuated Stressors.

A comparison for each agent shows that *Piet* gets into a sharp progression towards a high cognitive thought after direct exposure towards a heightened stressor. At the start of a high constant stressor, both individuals *Heidi* and *Kees* develop cognitive thought. However, after certain time points, those progressions dropped and reduced throughout time. As for *Piet*, even the stressors have been diminished; the level cognitive depressogenic thought was still high for several time points until it decreased.

Case # 3: Rapid Repeated Stressors with Different Individual Inferential Feedback and Situational Cues

For this simulation, each type of individual has been exposed to a stream of repeated stressors, with a rapid alteration between each event. In a real situation, it simulates the cumulative effect conditions, where repeated strikes had the effect of escalating the overall intensity of stressors.

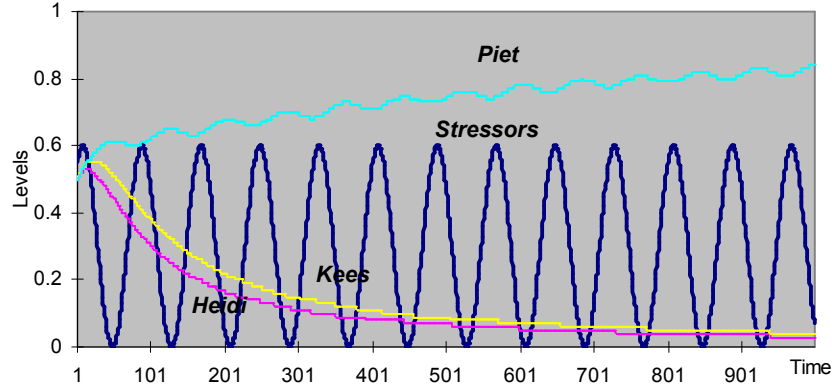


Fig. 4. Cognitive Depressogenic Level for Each Individual during Repeated Stressors.

Figure 4 illustrates the effects of repeated stressors condition towards different individuals. Note that *Piet* develops a gradual increasing level of cognitive thought, while both *Heidi* and *Kees* show a contrast effect. Using a similar experimental setting, by using $t_{max}=5000$, the end of the experimental results show *Piet* will have a persistent cognitive depressogenic value equal to 1.

5 Mathematical Analysis

By a mathematical formal analysis, the equilibria of the model can be determined. The equilibria explains condition where the values for the variables which no change occur. One important assumption should be made; all exogenous

variables are having a constant value. Assuming all parameters are non-zero, the list of LEADSTO specifications for the case of equilibrium for the agent X are:

$$dCd(t)/dt = (1-Cd) \cdot \phi \cdot (Hps-Cd) \cdot Cd \quad (1)$$

$$dHp(t)/dt = (1-Hp) \cdot \psi \cdot (MDi-Hp) \cdot Hp \quad (2)$$

Next, the equations are identified describing

$$dCd(t)/dt = 0, dHp(t)/dt = 0$$

Assuming both adaptation rates are equal to 1, therefore, these are equivalent to;

$$Cd=1 \text{ or } Hp=Cd \text{ or } Cd=0 \quad (3)$$

$$Hp=1 \text{ or } MDi=Hp \text{ or } Hp=0 \quad (4)$$

From here, a first of conclusions can be derived where the equilibrium can only occur when the $Cd=1$, $Hp=Cd$, or $Cd=0$ (refer to Equation 3). By combining these three conditions, it can be re-written into a set of relationship in $(A \vee B \vee C) \wedge (D \vee E \vee F)$ expression:

$$(Hp=1 \vee MDi=Hp \vee Hp=0) \wedge (Cd=1 \vee Hp=Cd \vee Cd=0) \quad (5)$$

This expression can be elaborated using the *law of distributivity* as $(A \wedge D) \vee (A \wedge E) \vee \dots \vee (C \wedge F)$. This later provides possible combinations equilibria points to be further analyzed. In this article, only condition $Cd=1$, $Cd=0$ have been chosen for the discussion. From this case ($Cd=1$), it can be further derived that respective values for the equilibrium condition to take place. These values can be calculated from the following formulae:

$$\begin{aligned} CDi &= \alpha \cdot MiF + (1-\alpha) \cdot (B \cdot Ne \cdot Cd) \cdot MiF \\ PS &= \eta \cdot AiF + (1-\eta) \cdot (1-(B \cdot Ne \cdot Cd)) \cdot AiF \\ SR &= \beta \cdot [\alpha \cdot MiF + (1-\alpha) \cdot (B \cdot Ne \cdot Cd) \cdot MiF] + (1-\beta) \\ MDi &= \gamma \cdot [\beta \cdot (\alpha \cdot MiF + (1-\alpha) \cdot (B \cdot Ne \cdot Cd) \cdot MiF) \\ &\quad + (1-\beta) \cdot (1-(\eta \cdot AiF + (1-\eta) \cdot (1-(B \cdot Ne \cdot Cd))) \cdot AiF)] \end{aligned}$$

This equilibria describes the condition when agents are experiencing an intense negative cognitive thought throughout time will eventually have their cognitive vulnerability level high to the limit. This condition creates higher vulnerability towards the development of onset during the present of negative events. It also represents the conditions where individuals with high maladaptive inferential feedbacks and situational cues levels over prolong period tend to develop cognitive depressogenic thought. Simulation trace from the experiment #1 confirms this condition. Another special case of an equilibrium condition is when $Cd=0$. In this case, the following values are found:

$$\begin{aligned} CDi &= \alpha \cdot MiF \\ PS &= \eta \cdot AiF \\ SR &= \beta \cdot (\alpha \cdot MiF) \end{aligned}$$

$$MDi = \gamma.\beta.(\alpha.(MiF).(1-\eta.AiF))$$

From this, it is an equilibrium, which would be considered as a good condition since the stable individuals' describes agents with a good mental condition (less vulnerable towards stressors). Having this, it shows that agents with high adaptive inferential feedbacks and low situational cues tend to have a low cognitive depressogenic thought level even during prolonged exposure towards stressors. Some parts of the simulation trace from the experiment #2 verify this condition. This condition is imperative to reduce the formation of potential relapse / recurrence caused by negative events. For the equilibrium case when $Hp=Cd$, the following values are found:

$$\begin{aligned} CDi &= \alpha.MiF + (1-\alpha).(B.Hp.Ne).MiF \\ PS &= \eta.AiF + (1-\eta).(1-(B.Ne.Hp)).AiF \\ SR &= \beta.(\alpha.MiF + (1-\alpha).(B.Hp.Ne).MiF) + (1-\beta).Hp \\ MDi &= \gamma.[\beta.(\alpha.MiF + (1-\alpha).(B.Hp.Ne).MiF) + \\ &\quad (1-\beta).Hp.(1-(\eta.AiF + (1-\eta).(1-(B.Ne.Hp)).AiF))] \end{aligned}$$

This equilibrium condition represents where the individuals remain constant in a cognitive depressogenic thought state over time points. Similarly, formulae can be derived for the other cases in Equation 5.

6 Automated Verification for the Domain Model

This section deals with the verification of relevant dynamic properties of the cases considered in the human agent model, which coherence with the literatures. The Temporal Trace Language (TTL) is used to perform an automated verification of specified properties against generated traces. TTL is designed on atoms, to represent the states, traces, and time properties. This relationship can be presented as a $state(\gamma, t, output(R)) \models p$, means that state property p is true at the output of role R in the state of trace γ at time point t [5]. Based on that concept, several dynamic properties can be formulated using a sorted predicate logic approach. Below, a number of them are introduced in semi formal and in informal representations.

VP1: Positive supports will reduce the risk in developing future depressogenic thought

When an agent X received more positive supports from its social support networks, then the agent will unlikely to develop further hopelessness in future.

$$\begin{aligned} VP1 &\equiv \forall \gamma:TRACE, t, t':TIME, R1,R2,R3,MIN_LEVEL:REAL, X:AGENT \\ &[state(\gamma, t) \models adapt_inf(X, R1) \ \& \ R1 > MIN_LEVEL \\ &\quad state(\gamma, t) \models cog_dep_tgt(X,R2) \ \& \ R2 > 0] \end{aligned}$$

$$\Rightarrow \exists t': \text{TIME} > t': \text{TIME}$$

$$[\text{state}(\gamma, t') | = \text{cog_dep_tgt}(X, R3) \ \& \ R3 < R2]$$

This property can be used to verify future condition of an agent if the agent receives positive supports from its social support members throughout time. Many research works have maintained that positive supports from members will decrease possibilities of having further negative thought in future [10].

VP2: Negative perception towards situation and bad support received from the social support networks will increase the risk of further depressogenic thought

When an agent X perceives all situations will give negative impact and an agent X receives bad support from its social support networks, then the agent X will almost likely to develop future depressogenic thought.

$$\text{VP2} \equiv \forall \gamma: \text{TRACE}, t, t': \text{TIME}, R1, R2, R3, R4, \text{MIN_MLD_LEVEL}, \text{MIN_SC_LEVEL}, \text{MAX_CDT_LEVEL}: \text{REAL}, X: \text{AGENT}$$

$$[\text{state}(\gamma, t) | = \text{maladap_bf}(X, R1) \ \& \ R1 > \text{MIN_MLD_LEVEL} \ \&$$

$$\text{state}(\gamma, t) | = \text{sit_cues}(X, R2) \ \& \ R2 > \text{MIN_SC_LEVEL} \ \&$$

$$\text{state}(\gamma, t) | = \text{cog_dep_tgt}(X, R3) \ \& \ R3 < \text{MAX_CDT_LEVEL}]$$

$$\Rightarrow \exists t': \text{TIME} > t': \text{TIME}$$

$$[\text{state}(\gamma, t') | = \text{cog_dep_tgt}(X, R4) \ \& \ R4 > R3]$$

By checking property VP2, one can verify whether negative perception (situational cues) and bad support will influence the rise of depressogenic thought. It is particularly significant to observe this property in the model given that bad support and negative perception is highly correlated towards the development of depressogenic thought [8].

VP3: Prolong exposure towards negative events, cognitive depressogenic thought, and bad support will increase the level of agent's cognitive vulnerability

When an agent X is experiencing prolong exposure towards negative events, high cognitive depressogenic thought, and bad support, then the cognitive vulnerability level of an agent X will be increased.

$$\text{VP3} \equiv \forall \gamma: \text{TRACE}, t, t': \text{TIME}, R1, R2, R3, R4, R5, \text{MIN_CDT_LEVEL}, \text{MIN_MLD_LEVEL}: \text{REAL}, X: \text{AGENT}$$

$$[\text{state}(\gamma, t) | = \text{neg_event}(X, R1) \ \& \ R1 > 0.7 \ \&$$

$$\text{state}(\gamma, t) | = \text{cog_dep_tgt}(X, R2) \ \& \ R2 > \text{MIN_CDT_LEVEL}$$

$$\text{state}(\gamma, t) | = \text{maladap_bf}(X, R3) \ \& \ R3 > \text{MIN_MLD_LEVEL}$$

$$\text{state}(\gamma, t) | = \text{cog_vulnerability}(X, R4) \Rightarrow$$

$$\exists t': \text{TIME} > t': \text{TIME}$$

$$[\text{state}(\gamma, t') | = \text{cog_vulnerability}(X, R5) \ \& \ R5 \geq R4]$$

This property can be used to check whether the cognitive vulnerability level will increase after a certain period of time, due to the exposure of above conditions.

7 Conclusion

In this paper, the assumed role of negative cognitive content in depression is explained. Based on this, a agent-model is presented that describes the temporal relation between personal characteristics, negative life events and social support. This model is used in a small simulation to investigate the effect of different types of support on different persons that undergo similar life events. The mathematical analysis of the model and the verification of expected behaviour of the modelled agents in the simulation traces give some evidence for the appropriateness of the model.

In the future, we would like to extent the model with the effect of negative thoughts and a bad mood on the willingness to offer support. Together with the existing elements of the model, this would allow for a multi-agent simulation of a larger community, in which different persons interact with each other by giving and receiving support. Such analysis would make it possible to investigate the consequences of depressive persons in a small community.

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Chapter 4

Simulating Cognitive Coping Strategies for Intelligent Support Agents

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“To survive you must surrender without giving in, that is to say, fully accept the reality in all its horror and never give up the will to survive. That allows you to quickly adapt to the situation and dedicate yourself to the present moment rather than wallow in denial. As you run out of options and energy you must become resigned to your plight. Like it or not you must make a new mental map of where you are, not where you wish you were. To survive you must find yourself, then it won't matter where you are.”

(Laurence Gonzales, Deep Survival: Who Lives, Who Dies, and Why)

Simulating Cognitive Coping Strategies for Intelligent Support Agents

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Abstract: People react differently to stress. According to the Cognitive Motivational Relational Theory by Lazarus and Folkman, the appraisal of stress and the emotions related to it determine whether people cope with stress by focussing on altering the situation (problem focussed) or on changing the emotional consequences of the events (emotion focussed). These different coping strategies have different effects on the long term. The coping process can be described in a formal dynamic model. Simulations using this model show that problem focussed coping leads to better coping skills and higher decrease of long-term stress than emotion focussed coping. These results also follow from a mathematical analysis of the model. The presented model can form the basis of an intelligent support system that uses a simulation of cognitive processes in humans in stressful conditions.

Keywords: virtual human agent model, stress, cognitive and behavioral modeling, and temporal dynamics.

1 Introduction

Stress is simply a reality of nature where forces from the outside world affecting the individual. It comes in many forms and affects people of all ages and all walks of life. The individual responds to stress in ways that affect the individual as well as their environment. Hence, all living creatures are in a constant interchange with their surroundings, either physically or behaviorally. In general, stress is generally considered as being synonymous with distress and dictionaries defined it as “physical, mental, or emotional strain or tension” or “a condition or feeling experienced when a person perceives that demands exceed the personal and social resources the individual is able to mobilize” [4][7]. However, human has its own mechanism to adapt with this adversity. Through a process known as coping, our cognitive skill will evaluate the situation mentally. If the situation is threatening, then the human will decide how to deal with the situation, and what skills can be used. If the demands of the situation outweigh the resources human has, then it will be labeled as “stressful” and he or she will react with the classical stress response and vice versa [5]. It is essential to consider that everyone sees situations differently and has different coping skills. For this reason, no two people will respond exactly the same way to a given situation.

Understanding this coping ability is an essential ingredient for developing a software agent that is capable of providing the right intervention towards stressed individuals [1]. Therefore there is a need for a virtual human agent model that has this capability. In this paper, virtual human agents are computer model of people that can be used as substitutes for “the real person” in a virtual environment, with a specific focus on simulating human coping behaviors during the formation of stressful events. Although there has been several work in computational models of human stress, little work has been done in modeling coping strategies, with a few exceptions in [12][13].

This paper focuses exclusively on the formal model for dynamics in coping process, as it is one of the essential components in the development of a software agent that is able to monitor individuals’ conditions during stressful events [2]. In the next section, the underlying principles in coping during stress are discussed (Section 2). From this perspective, a formal model is designed and formulated (Section 3). Later, in Section 4, simulation traces are presented to illustrate how this model satisfies the expected outcomes in long-term stress. In Section 5, a detailed mathematical analysis is performed, to identify equilibria in the model. Finally, Section 6 concludes the paper.

2 Underlying Concepts in Coping

The cognitive theory that governs the underlying principle of this work is based on Cognitive Motivational Relational Theory (CMRT) as in [10]. This theory explains the role of distinctive positive and negative emotions in the stress

appraisal process. Essentially, it conceptualized a transactional process in which the person and the environment are viewed as being in a dynamic and bidirectional relationship, where the essence of cognitive appraisal and coping provides a critical mediator between stressful person-environment and health outcomes.

2.1 Dynamics in Cognitive Appraisal Process and Coping Strategies

The cognitive approach to coping is based on a mental process of how the individual appraises the situation. Cognitive appraisal can be viewed as the evaluation of the significance of what is happening in the person-environment relationship [11]. Normally, it is also related to the *intensity of the stressful events*, a condition where several factors such as *situational demands* (pressure), *personal resources* (i.e; support), and *negative events* play important roles [3][10]. Having the stressful events in motion, individual appraises two types of appraisals; the primary and the secondary. The primary appraisal is made when the individual makes a conscious evaluation of the matter at hand of whether it is a sense of harm or a loss, a threat or a challenge. It is an evaluation process of what is at stake for a person's well being. From this first process, the situation can be appraised either as harm/loss, threatening, challenging or benign [7]. *Harm* or loss refers to a condition where damage has already occurred, while *threat* refers to damage, but an anticipated one (*imminence of harm*) and it is more to a risk assessment part [9]. *Challenging* differs from threat in term of how persons are viewing it where it has a positive tone compared to threat. When stressful events were appraised as irrelevant or as *benign*, it will offer the chance to preserve or enhance wellbeing as it does not initiate the stress process as there is no potential threat to overcome. In addition, this appraisal process also involves an array of *personality attributes* such as values, commitments, and beliefs about oneself and the environment in defining the condition that the individuals are facing through [17]. Later this process will determine individuals' emotion perception; *negative*, *positive* or *neutral* emotion [8]. Negative emotion is related to perceiving *harm* and *threat*, while positive emotion is attributed to perceiving *challenge* [11]. Neutral emotion is triggered when individual perceives the condition as *benign* [14].

In the second appraisal, the persons evaluate whether they have the resources to deal with the incoming stressors. It is commonly related to the emotional attribution, where a positive and neutral emotion results in *acceptance* and *change*, while the negative emotion triggers *holdback* behavior [11]. During this stage, several coping strategies are evaluated. Coping strategies refer to the specific efforts, both behavioral and psychological, that people employ to either be in charge of, tolerate, reduce, or minimize stressful events. According to the CMRT model, there are two types of coping strategies have been distinguished, namely; *problem-focused coping* and *emotion-focused coping*. A problem-focused coping is associated with aggressive interpersonal efforts to alter the situation, as well as

rational efforts to get the problem solved [5]. Contrary to this, emotion-focused coping strategies (thinking rather than acting to change the person-environment relationship) entail efforts to regulate the emotional consequences of stressful or potentially stressful events [16]. It is typically include distancing, escape avoidance, and seeking for social comforts.

Several findings showed that the type of coping strategies can be derived, depending on what was at stake (primary appraisal) and what the coping options were (secondary appraisal) [11][15]. It means, when people feel that they are capable of changing the situation into something better (high perception of acceptance and change), and then a problem-focused coping is chosen. In contrast, when the conditions are considered not amenable to change (high perception in holdback) then emotion-focused coping is used. In addition to this, problem focused coping strategies may give an individual greater perceived control over their problem, while emotion focused coping strategies may more often lead to a reduction of control over the perceived events. All these strategies can be proven useful, but many individuals feel that problem-focused coping represent a more effective means of coping in adversities [17]. In addition to this, in a long run, emotion focused coping is associated with outcomes that people found unsatisfactory (*exhaustion in coping*) that later will increase long-term stress, and problem focused coping is associated with satisfactory outcomes (*improved coping skills*) [6]. Furthermore, in psychological distress, problem focus coping strategies appear reliably to produce better emotional adjustment to chronically stressful events than do emotional focused strategies [16][17].

In short, the following dynamics can be identified from the literature; (1) the intensity of the stressful events will lead to coping appraisal, (2) the perception of event regulates emotional attribution, (3) the emotional attribution will trigger a coping strategy, (4) a long-term overwhelming dependency in emotion-focused coping will lead to the exhaustion in coping, and (5) a problem-focused coping will improve the coping ability.

3 The Virtual Human Agent Model

Based on the analysis of the cognitive dynamics in coping appraisal and strategy as given in the previous section, it is possible to specify computational properties for the virtual human agent model. These computational properties are represented in a way that allows simulating how an individual is coping when experiencing stressors, and what are the consequences of that action. All of these concepts (and their interactions) are discussed in the following paragraphs in this section.

3.1 Formalizing the Cognitive Model Relationships

In the formalization, the dynamic concepts discussed in the previous section are translated into several interconnected nodes. Figure 1 depicts the global interaction between these nodes. The nodes are represented as variables that can have values ranging from 0 (low) to 1 (high). The interaction will determine the new value of it, either by a series of accumulations or an instantaneous interaction for each node.

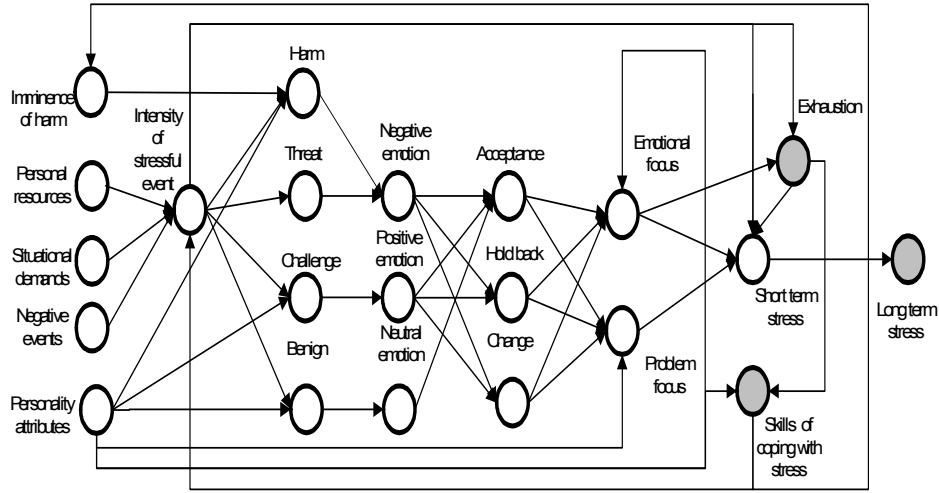


Fig. 1. Global Relationships of Variables Involved in the Coping Process.

The description of these formalizations is described in the following. Together, this results in a dynamic model. This model involves a number of instantaneous and some temporal relations. The dark nodes represent concepts that have temporal relationships with the incoming nodes, in which the change is specified for a time interval between t and $t + \Delta t$

Stressor Events, Intensity of Stressful Event, and Imminence of Harm

In the model, the stressor events (e) (negative events) are generated by simulating potential effects throughout t time using w weighted sum of three types of events; life (le), chronic (ce), and daily (de) events. The role of these factors in the model is to represent a series of events. The intensity of stressful event (IsE) represents the degree of stress encountered by a person related to his or her situational demands (SiD), and stressor events ($NeVt$), regulated by the proportion factor β_e . In addition, the intensity of a stressful event will be reduced if the coping skills (ScS) and personal resources (PeS) are high. Imminence of

harm (ImH) can be measured by combining both concepts in perceived harm (PeH) (from the environment), and coping skills (ScS).

$$NeV(t) = w_1.le(t) + w_2.ce(t) + w_3.de(t), \sum w_i = 1 \quad (1)$$

$$IsE(t) = [\beta_e.NeV(t) + (1-\beta_e).SiD(t)].(1-ScS(t)).(1-PeS(t)) \quad (2)$$

$$ImH(t) = PeH(t).(1-ScS(t)) \quad (3)$$

Harm, Threat, Challenge, and Benign

The level of harm (HrM) is determined by the proportional contribution ϕ_b on the imminence of harm, and intensity of the stressful event. The intensity of the stressful event also related to threat (TbT). For both cases, in harm and threat, there is a negative relation with personality attributes. On the contrary, challenge (ChL) and benign (BnG) are positively related with good personality attributes (PrA), and negatively with the intensity of stress. Here parameters α_c and ψ_b represent the proportional factor for both challenge and benign respectively.

Negative, Neutral, and Positive Emotion

$$HrM(t) = [\phi_b.ImH(t) + (1-\phi_b).IsE(t).ImH(t)].(1-PrA(t)) \quad (4)$$

$$TbT(t) = IsE(t).(1-PrA(t)) \quad (5)$$

$$ChL(t) = \alpha_c.PrA(t) + (1-\alpha_c).(1-IsE(t)).PrA(t) \quad (6)$$

$$BnG(t) = \psi_b.(1-IsE(t)) + (1-\psi_b).PrA(t) \quad (7)$$

When the harm and threat is perceived, a fraction from those two parts (by a proportional factor β_n) is contributed as a negative emotion (NgE). The notion of positive (PsE) and neutral (NuE) emotion is represented through a proportional factor of τ_p in challenge and ρ_c in benign respectively.

$$NgE(t) = \beta_n.HrM(t) + (1-\beta_n).TbT(t) \quad (8)$$

$$PsE(t) = \tau_p.ChL(t) \quad (9)$$

$$NuE(t) = \rho_c.BnG(t) \quad (10)$$

Acceptance, Holdback, and Change

Positive and neutral emotion increases the acceptance (AcP) level by a proportional factor γ_n , while negative emotion works in a opposite way. Holdback (HdB) depends on the relation between negative and positive emotion. Change (ChG) uses the same concepts as in holdback but with the opposite relation.

$$AcP(t) = \gamma_a.PsE(t) + (1-\gamma_a).NuE(t).(1-NgE(t)) \quad (11)$$

$$HdB(t) = (1-PsE(t)).(NgE(t)) \quad (12)$$

$$CbG(t) = PsE(t).(1-NgE(t)) \quad (13)$$

Emotional and Problem Focused Coping

Emotional focused coping (EmF) is determined using the presence of acceptance, holdback and change. Using this relation, emotion focused coping decreases when either acceptance or change increases. However in problem focused coping (PrF), coupled with personality attributes, those factors provide a positive effect. Parameters η_e and γ_p regulate the contribution preferences for both specifications respectively.

$$EmF(t) = [\eta_e.(1-AcP(t)).HdB(t) + (1-\eta_e).HdB(t)].(1-CbG(t)) \quad (14)$$

$$PrF(t) = [\gamma_p.PrA(t) + (1-\gamma_p).AcP(t)].(1-HdB(t)).CbG(t) \quad (15)$$

Short-term stress, Long-term stress, Exhaustion, and Coping Skills

The notion of short-term stress (StS) models a relation between coping styles (regulated by μ_s), and a combination of exhaustion and intensity in stressful events (regulated by a proportional rate γ_s) and will influence the level of long-term stress (LtS) in a long run. The formation of exhaustion (ExH) is modelled using the presence of emotion-focused coping and the intensity of stressful events. The level of coping skills (ScS) is influenced by the exhaustion and personality attributes. The rates of change for all temporal relationships are determined by flexibility parameters β_{ls} , ψ_e and ϕ_s respectively.

$$StS(t) = [1-(\mu_s.EmF(t) + (1-\mu_s).PrF(t))].(\gamma_s.ExH(t) + (1-\gamma_s).IsE(t)) \quad (16)$$

$$LtS(t+\Delta t) = LtS(t) + \beta_{ls}.[Pos(StS(t)-LtS(t)).(1-LtS(t)) - Pos(-(StS(t)-LtS(t))).LtS(t)].\Delta t \quad (17)$$

$$ExH(t+\Delta t) = ExH(t) + \psi_e.[Pos((IsE(t)-ExH(t)).(1-ExH(t))) - Pos(-(IsE(t)-ExH(t)).ExH(t))].EmF(t).\Delta t \quad (18)$$

$$ScS(t+\Delta t) = ScS(t) + \phi_s.[Pos(ExH(t) - ScS(t)).(1-ScS(t)) - Pos(-(ExH(t) - ScS(t)).ScS(t)).PrA(t)].\Delta t \quad (19)$$

The operator Pos for the positive part is defined by $Pos(x) = (x + |x|)/2$, or alternatively; $Pos(x) = x$ if $x \geq 0$ and 0 else.

4 Example Simulation Traces

In this section, the virtual human agent model of coping has been executed to simulate a number of scenarios with a variety of different conditions of

individuals. Two example scenarios are shown: an individual with a tendency to choose problem focused coping (**A**), and an individual with a tendency to choose emotional focused coping (**B**). The initial settings for the different individuals are the following (PrA , PeH , SiD , PeS); **A** (0.8, 0.5, 0.5, 0.8), and **B** (0.2, 0.5, 0.8, 0.1). In all cases, the long term stress, exhaustion, and coping skill value are initialized at 0.3. Corresponding to these settings, the level of severity is set at 0.5, defining that any individuals scoring higher than 0.5 in their long-term stress and exhaustion levels will be considered as experiencing difficulties in coping. These simulations used the following parameters settings: $t_{max}=1000$ (to represent a monitoring activity up to 42 days), $\Delta t=0.3$, all proportional and flexibility rates are assigned as 0.5 and 0.9 respectively. These settings were obtained from several systematic experiments to determine the most suitable parameter values in the model.

Result # 1: Simulation Trace for Repeated Stressor Events

During this simulation, each type of individual has been exposed to an extreme stream of stressor events, with a moderate alteration between each corresponding event. Figure 2 depicts the comparison between the conditions of individual **A** and **B** during repeated stressors. In this simulation trace, it is visible that individual **A** has developed better coping skills. For this reason, an individual **A** recovers much faster from long-term stress compared to other individuals.

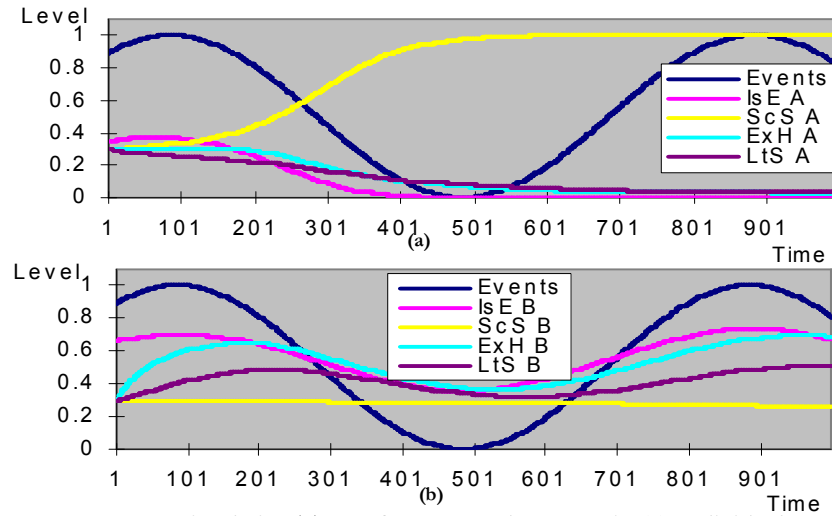


Fig. 2. Simulation Traces for Repeated Stressor in (a) Individual **A**
(b) Individual **B**.

Note that the individual B shows a repeated increasing pattern that may lead to potential long-term stress. As a consequence of this condition, an individual B will experience difficulty if that individual is having constant exposure towards stressors in a long run.

Result # 2: Simulation Trace for Fluctuated Stressor Events This simulation trace shows two types of periods, one with a very high constant and with a very low constant stressor event. These events occurred in a constant behaviour for a certain period of time (approximately within 20 days).

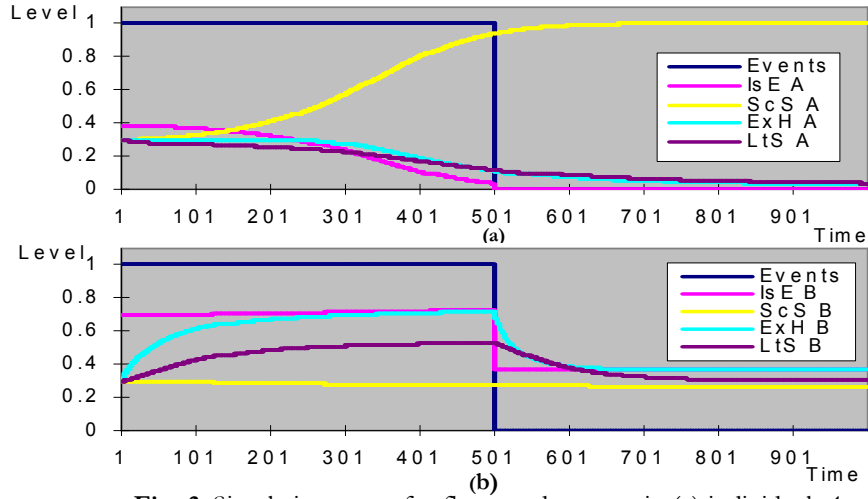


Fig. 3. Simulation traces for fluctuated stressor in (a) individual A (b) individual B .

Also here it can be seen (in Figure 3) that individual B gets into long-term stress much faster than individual A . Moreover, even at the end of the simulation time, the long term stress level of individual B is still slightly higher than individual A . Furthermore, in contrast with individual B , individual A has his/her coping skills improved throughout time.

5 Mathematical Verification

This section addresses the formal analysis of the agent model and the simulation results presented above by means of a mathematical analysis of the equilibria of the model. The equilibria describe situations in which a stable situation has been reached. Those equilibria are interesting as it should be possible to explain them using the knowledge of the domain that is modelled [2]. As such, the existence of

reasonable equilibria is an indication for the correctness of the model. To analyze the equilibria, the available temporal and instantaneous equations are filled with values for the model variables such that the derivatives or differences between time point t and $t + \Delta t$ are all 0. The dynamic part of the model written in differential equation format is as follows:

$$dLs(t)/dt = \beta_{ls} [\text{Pos}(StS(t)-Ls(t)).(1-Ls(t))-\text{Pos}(-(StS(t)-Ls(t))).Ls(t)] \quad (20)$$

$$dExH(t)/dt = \psi_e [\text{Pos}(IsE(t)-ExH(t)).(1-ExH(t))-\text{Pos}(-(IsE(t)-ExH(t))).ExH(t)].EmF(t) \quad (21)$$

$$dScS(t)/dt = \phi_s [\text{Pos}(ExH(t)-ScS(t)).(1-ScS(t))-\text{Pos}(-(ExH(t)-ScS(t))).ScS(t)].PrA(t) \quad (22)$$

For an equilibrium it has to hold that all of the derivatives are zero:

$$dLs(t)/dt = dExH(t)/dt = dScS(t)/dt = 0$$

Assuming β_{ls} , ψ_e and ϕ_s nonzero, this provides the following equilibrium equations:

$$\begin{aligned} \text{Pos}(StS-Ls).(1-Ls) &= 0 \\ \text{Pos}(-(StS-Ls)).Ls &= 0 \end{aligned}$$

Table 1 shows which cases can be distinguished. For example, notice that always $\text{Pos}(x) \geq 0$, so (23) is equivalent to:

$$\text{Pos}(StS-Ls).(1-Ls)-\text{Pos}(-(StS-Ls)).Ls = 0 \quad (23)$$

$$[\text{Pos}(IsE-ExH).(1-ExH)-\text{Pos}(-(IsE-ExH)).ExH].EmF = 0 \quad (24)$$

$$[\text{Pos}(ExH-ScS).(1-ScS)-\text{Pos}(-(ExH-ScS)).ScS].PrA = 0 \quad (25)$$

This provides cases:

$$(StS \leq Ls \vee Ls = 1) \wedge (StS \geq Ls \vee Ls = 0) \quad (26)$$

This can be logically rewritten into:

$$\begin{aligned} (StS \leq Ls \wedge StS \geq Ls) \vee (StS \leq Ls \wedge Ls = 0) \vee \\ (Ls = 1 \wedge StS \geq Ls) \vee (Ls = 1 \wedge Ls = 0) \end{aligned}$$

The latter case cannot exist, and as $0 \leq StS \leq 1$ the other three cases are equivalent to $StS = Ls$. Similarly the cases for (24) and (25) can be found as shown in Table 1.

Table 1. Equilibrium Equations.

(1)	(2)	(3)	Combined
$StS = LtS$	$EmF = 0$	$PrA = 0$	$StS = LtS$, $EmF = PrA = 0$
		$ExH = ScS$	$StS = LtS$, $EmF = 0$, $ExH = ScS$
	$IsE = ExH$	$PrA = 0$	$StS = LtS$, $IsE = ExH$, $PrA = 0$
		$ExH = ScS$	$StS = LtS$, $IsE = ExH = ScS$

Note that for each of the distinguished cases, further information can be found about the equilibrium values of other variables using the other non-dynamic-equations. For example, from $EmF = 0$ by (14) it follows that $ChG = 1$ or $HdB = 0$. This condition illustrates the generic condition that a problem-focused individual that encounters stressful events will never develop long term stress that typically caused by a prolonged dependency on emotion-focused focus coping [2][15][16]. From another condition $PrA = 0$, by (6) it follows that $ChL = 0$ represents a condition when an individual with negative personality attributes tend to appraise stressful events not as a challenge later will trigger emotion-focused coping [6][17]. Both of these conditions can be found in our simulation results.

6 Conclusion

In this paper, we have presented a formal temporal model for the cognitive process of coping with stress as described in the informal Cognitive Motivational Relational Theory by Lazarus and Folkman. This theory explains the role of positive and negative emotions in the stress appraisal process, which results in either a problem focused coping strategy or an emotional focused coping strategy. The theory also describes the effect of the different strategies on the long term stress.

The resulting model has been used for two simulations of two persons with different personality characteristics in two different scenarios that describe the level of external sources of stress over time. The simulation traces exhibit patterns that are expected in this domain: problem focused coping leads to better coping skills and higher decrease of long-term stress than emotion focused coping. These results also follow from a mathematical analysis of the model, in

which the equilibria of the model are determined to identify the stable situation in the model.

The resulting model can be considered as a virtual human agent model, in the sense that it is a computer models of a person that can be used as a substitute for the real person in a virtual environment. This could provide the basis for a intelligent support system, in which the system should be able to understand the coping process of the persons to which support is provided.

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Part III

Ambient Agent Models to Support a Person with a Risk of Unipolar Depression

Chapter 5

Modeling an Ambient Agent to Support Unipolar Depression Relapse Prevention

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“As technology advances, it reverses the characteristics of every situation again and again. The age of automation is going to be the age of ‘do it yourself.’”

(Marshall McLuhan, Essential McLuhan)

Modeling an Ambient Agent to Support Depression Relapse Prevention

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Abstract: One of the challenges for the patients with a history of unipolar depression is to stay healthy throughout their lifetime. In principle, with more prior onset cases, it escalates the risk of the patients to fall into a relapse. In this paper, an ambient agent based model to support patients from relapse is presented. Theories and related works in depression relapse prevention provide a foundation for the formalization of the temporal properties to describe the model. This model was analyzed under several scenarios using simulation and automated verification.

Keywords: ambient agent, unipolar depression relapse modelling, decision support model, temporal modelling.

1 Introduction

Depression carries in many terms and severity symptoms. Primarily, it can be triggered by life events and have an acute onset (within days or weeks). Despite of many pharmaceutical and holistic interventions, depression still has a high rate of relapse and recurrence [10]. Relapse is defined as “episode of major depressive disorder that occurs within six months after either response or remission (no longer meeting the depression criteria)” [11]. Reviewing studies of lifetime course of depression concluded that, the risk of repeated onset exceeds more than 60 percent for any individuals who have had one previous episode, and with the rate of 58 percent to strike back after 5 years of recovery [15][17]. Therefore, it is a need to have system that capable to support patient in a long term.

One of the main quests to have such a system is the ability to monitor patients’ behaviours and changes using information related to them. To realize the quest, an ambient intelligent agent model was developed, and to be used to monitor patients’ state over time. This kind of agent utilizes ambient sensor information about human, and their functioning to improve human’s wellbeing. The agent model was designed using a set of dynamic properties, takes observations as input, and belief-desire-intention concept to determine its internal function and actions. Dynamic properties have been developed and formalized to model how humans are experiencing relapse. Using this information, the model was simulated and verified.

This paper is structured as follows. In the following, the model of an ambient agent is described. It covers several sub-models used as a building block of the model. Subsequently, the main concepts of this model are specified, and as a result, a formal presentation is designed. Later, results from simulation experiments are discussed and verified. Finally, a discussion concludes this paper.

2 Overview Of The Ambient Agent Model

A typical cause of relapse is a condition called the stressors. These stressors may derive from life, chronic, or daily events. The culmination of these factors will become overwhelming and leave a person feeling that they have lost control of their life. Such conditions can be observed through several ambient sensors and devices, namely; a medicine box that registers medication intake (MEMS) [6], a passive alcohol sensor [12], a mobile phone/personal digital assistant (PDA) [5], and a blood volume pressure sensor [14][18]. The overall process of relapse monitoring has been modelled by using an ambient agent model. Four components are integrated to build the model, namely; domain model, belief base, analysis model and support model [2]. Figure 1 illustrates an overview of the entire ambient agent model.

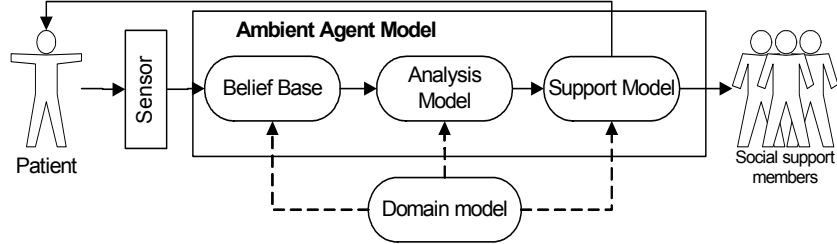


Fig. 1. The Integration of the Components.

From Figure 1, the solid arrow indicates information exchange between processes, and the dotted arrow represents the integration process of the domain model within the ambient agent models.

2.1 Domain Model

The observable factors that explain the progression of relapse are among key aspects to develop the domain model. This model uses the main factors of recurrence and relapse of depression as known from the literature. These factors are avoidant coping, social withdrawal, prolonged anxiety (neurotic), low in assertiveness, and high vulnerability towards relapse [7]. By coupling these concepts, a model to explain the phenomena of relapse was developed. Our previous work in human's relapse and recurrent model explains the temporal dynamics and interactions among those related factors existed prior to the onset [1]. Figure 2 summarizes the interaction among these factors used in the domain model.

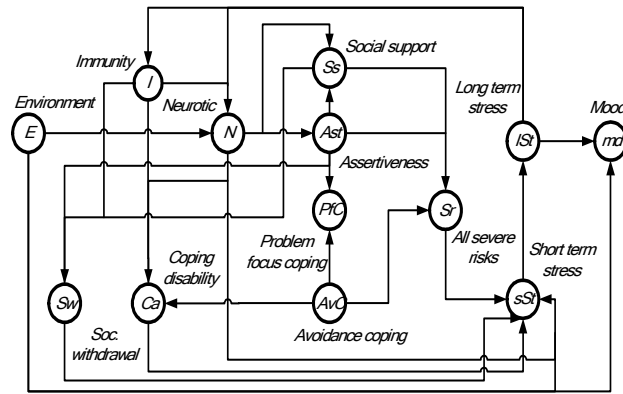


Fig. 2. Relationship of Factors Involved in Relapse.

The simulation results have shown the model exhibits important patterns between the events and the course of relapse and recurrence. From several simulation runs, the domain model demonstrates three distinctive features in relapse/recurrence; (i) stressor events directly trigger the potential onset of relapse/recurrence, (ii) neuroticism escalates the effect of stressor events on the potential relapse / recurrence of a depression; and (iii) a combination of positive social support and coping skills will reduce the risk of having future relapse/recurrence [1][10][13][17]. In order to implement related concepts from the domain model, three sub-models were designed within an ambient agent model, namely; belief base, analysis, and support model. In this model, desire to reduce the relapse is added as a desire refinement, to support the decision making process during relapse prevention. It derives another desire to perform intention to support patient. The relationship between these two desires can be described as

$$\forall K:\text{TASK}, \forall X:\text{AGENT} \\ \text{desire}(X, \text{reduced}(\text{risk_relapse})) \rightarrow \text{desire}(K)$$

Furthermore, during this process, the agent considers temporal, causal, and other relation between the observable events to recognize the most suitable action, which describes possible solution for state of the patient at a specific time. The details of these sub-models can be found in [2].

3 Formalizing Dynamic Properties

To specify properties on dynamics relationship, the ontology of the model is designed using predicate calculus. For example, any agent ability to observe the frequency level of pill intake can be expressed as `observed(X:AGENT, pill_intake,(F:FREQ_LEVEL))`.

Ontology for Agent's Observation: Observation using several sensors (input from patient-world interaction). The agent observes human's condition through pill intake activities, alcohol compound in a blood stream, blood pressure level, phone usages, and social interaction with the social group.

```
observed(X:AGENT, pill_intake(F:FREQ_LEVEL))
observed(X:AGENT, alcohol_level(L:LEVEL))
observed(X:AGENT, BVP_level(L:LEVEL))
observed(X:AGENT, phone_usage(T:TYPE))
observed(X:AGENT, social_activity(T:TYPE))
```

Ontology for Belief Base: *Basic belief* (generated belief after several observations on pill intake, alcohol level reading, social activities, phone usage, and blood volume pressure reading)

```
belief(X:AGENT, pill_intake(F:FREQ_LEVEL))
belief(X:AGENT, alcohol_level(L:LEVEL))
belief(X:AGENT, BVP_level(L:LEVEL))
belief(X:AGENT, phone_usage(T:TYPE))
belief(X:AGENT, social_activity(T:TYPE))
```

Derived belief (belief on substance abuse, avoidant coping, neurotic, social support, immunity and assertiveness)

```
belief(X:AGENT, sub_abuse(L:LEVEL))
belief(X:AGENT, avoidant_coping(L:LEVEL))
belief(X:AGENT, neurotic(L:LEVEL))
belief(X:AGENT, social_support(T:TYPE))
belief(X:AGENT, immunity(L:LEVEL))
belief(X:AGENT, assertiveness(L:LEVEL))
```

Ontology for Analysis Model: There are three levels of analysis used; evaluation on coping skills, social withdrawal, and severe risk factors. These distinctive features provide important information to execute a specific action in the support model.

```
assessment(X:AGENT, coping_skill(L:LEVEL))
assessment(X:AGENT, social_interaction(L:LEVEL))
assessment(X:AGENT, all_factors(L:LEVEL))
prediction(X:AGENT, stage(C:COND, T:TYPE))
```

Ontology for Support Model: Two main actions are used to intervene the risk of relapse namely; notify and advice. The BDI approach regulates action selection process (internal processing) [9]. An action to be taken by an ambient agent is represented using *performed* as its predicate.

```
belief(X:AGENT, seek(K:TASK))
desire(X:AGENT, improved(K:TASK))
desire(X:AGENT, reduced(C:COND))
intention(X:AGENT, advice(K:TASK))
intention(X:AGENT, notify(R:ROLE))
performed(X:AGENT, advice(K:TASK))
performed(X:AGENT, notify(C:COND, R:ROLE))
belief(X:AGENT, stage(C:COND, T:TYPE))
```

The formalization of some properties makes use of sorts. These sorts are presented in Table 1.

Table 1. Sort Used.

Sort	Elements
LEVEL	{low, medium, high}
TYPE	{positive, negative}
FREQ_LEVEL	{normal, not_taken, overdose}
TASK	{avoid_substance_abuse, social_activities, relaxation_activities, coping_skills, meet_doctor_therapist}
ROLE	{patient, friends_family, doctor_therapist}
AGENT	{low, medium, high}
COND	{risk_relapse, anxiety, healthy}

In order to specify simulation model, a temporal specification language has been used. This language called as LEADSTO enables one to model direct temporal relationship between two state properties (dynamic properties). Consider the format of $\alpha \rightarrow_{e,f,g,h} \beta$, where α and β are state properties in form of a conjunction of atoms (conjunction of literals) or negations of atoms, and e,f,g,h represents non-negative real numbers. This format can be interpreted as follows;

If state α holds for a certain time interval with duration g , after some delay (between e and f), state property β will hold a certain time interval of length h .

Here, atomic state properties can have a qualitative, logical format to represent certain observed conditions. In addition, this representation also holds a temporal trace γ , denoted by $\gamma \models \alpha \rightarrow_{e,f,g,h} \beta$, if

$$\begin{aligned} & \forall t_1 [\forall t_1 [t_1 - g \leq t < t_1 \Rightarrow \alpha \text{ holds in } \gamma \text{ at time } t] \\ & \Rightarrow \exists d [e \leq d \leq f \ \& \\ & \quad \forall t' [t_1 + d \leq t' < t_1 + d + h] \Rightarrow \beta \text{ holds in } \gamma \text{ at time } t'] \end{aligned}$$

For a more detailed discussion of this language, see [3]. It is worth to mention in this paper, LEADSTO is mainly used as a modelling instrument. It also possible to be implemented with any related tool.

3.1 Temporal Specification of the Ambient Agent

The temporal rules specification of an ambient agent has been specified using the ontology. Each specification is designed to provide a set of knowledge for an

ambient agent to reason with. To utilize the specification, a forward method for belief generation is used. This way of reasoning allows the time sequence and causality, originated from beliefs about related properties at certain previous time point, and new beliefs about properties at later time points. The ambient agent functionality is described by three actions; belief generation in belief base, evaluation of risk, and action selection for the support. For example, in a social withdrawal case, the ambient agent observes the patient's condition and generates its monitoring beliefs at the belief base. In belief base, these properties are identical with the observed one. It can be generalized as;

IF ambient agent X observes Y, THEN ambient agent X will believe Y.
 $\text{observed}(X, Y) \rightarrow \text{belief}(X, Y)$

The following properties show several temporal specifications in social withdrawal condition.

BEL4: Generating basic belief on phone/PDA usage

When the ambient agent observes there is no phone/PDA usage, then the agent believes that a patient is not using phone/PDA to communicate with the others.

$\text{observed}(\text{agent}, \text{phone_usage}(\text{negative})) \rightarrow \text{belief}(\text{agent}, \text{phone_usage}(\text{negative}))$

DB1: Derived belief on social support from the phone usage belief

If the ambient agent believes that there is no phone usage then the agent will believe there is no social interaction between social support network members.

$\text{belief}(\text{agent}, \text{phone_usage}(\text{negative})) \rightarrow \text{belief}(\text{agent}, \text{social_support}(\text{negative}))$

Then, in order to reason about the observed belief, this information is interpreted in the analysis model.

AE2: Evaluation on social withdrawal condition

If it is believed that patient is not interacting with any social network support members, and having difficulty to control anger and it is believed that patient is vulnerable for the future onset then the agent concludes that the condition of the patient as having social withdrawal.

$\text{belief}(\text{agent}, \text{social_support}(\text{negative})) \wedge \text{belief}(\text{agent}, \text{assertiveness}(\text{low})) \wedge \text{belief}(\text{agent}, \text{immunity}(\text{low})) \rightarrow \text{assessment}(\text{agent}, \text{social_interaction}(\text{low}))$

PR3: Predicting the risk of relapse from social withdrawal condition

If the patient is having social withdrawal then the ambient agent will assesses the patient as having potential risk of relapse.

assessment(agent, social_interaction(low)) → prediction(agent,
stage(risk_relapse, positive))

Finally, the ambient agent will utilize specified temporal rules in the support model to take appropriate actions.

BEL2: Belief on relapse

When the ambient agent predicts the patient is having a risk in relapse, then the ambient agent will believe the patient is in the risk of relapse.

prediction(agent, stage(risk_relapse, positive)) → belief(agent,
stage(risk_relapse, positive))

ACT2: Action to notify social support networks

When the ambient agent believes the patient in the risk of relapse then the ambient agent will notify all friends and family within social support network.

belief(agent, stage(risk_relapse, positive)) →
performed(agent, notify(risk_relapse, friends_family))

ACP1: Action to notify the patient

When the ambient agent believes the patient in the risk of relapse then the ambient agent will notify the patient.

belief(agent, stage(risk_relapse, positive))
→ performed(agent, notify(risk_relapse, patient))

DES2: Desire to improve social interaction

If the ambient agent assesses the patient is having social withdrawal then the ambient agent will desire to improve patient's social interaction by advising the patient about suitable social activities.

assessment(agent, social_interaction(low)) ∧ desire(agent,
reduced(risk_relapse)) → desire(agent, improved(social_activities))

INT3: Intention to advice on social interaction

When the ambient agent desires to improve patient's social interaction through social activities and ambient agent believes there is no social interaction between a patient and social support network members, then ambient agent will have an intention to advice patient on suitable social activities.

desire(agent, improved(social_activities)) ∧
belief(agent, social_support(negative))
→ intention(agent, advice(social_activities))

ACT6: Action to advice on social interaction activities

When the ambient agent intends to advice the patient regarding to social activities to the patient, then the ambient agent will advice the patient about those social activities.

```

intention(agent , advice(social_activities))
→→performed(agent , advice(social_activities))

```

4 Simulation Results

Based on the proposed model, using the specified temporal rules to determine the stage of patient, several simulations have been performed. For this paper, three examples of simulation runs were chosen. In the figures below, timeline is shown on the horizontal axis, the state properties are on the vertical axis and a dark box indicates that a state property is true.

Simulation # 1: Social Withdrawal

This condition occurs when the ambient agent observes no activities in social interaction, low in assertiveness, and highly vulnerable towards future onset. The patient is highly advised to engage social interaction with others [16]. Having this in motion, social support network members will be informed by an ambient agent (see Figure 3).

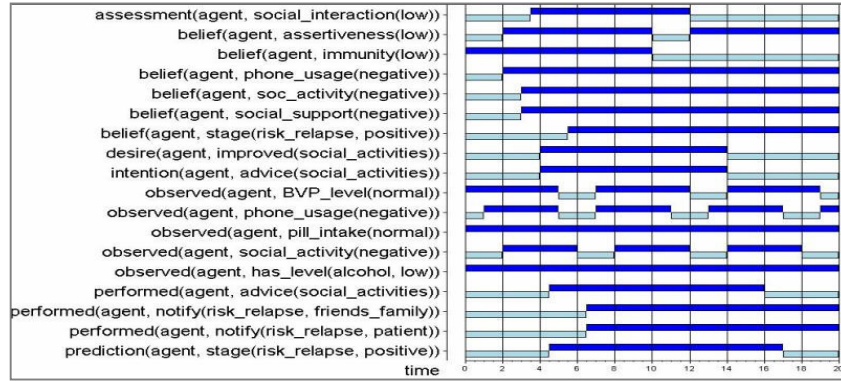


Fig. 3. Simulation Trace in Social Withdrawal.

Simulation #2: Deficiencies in Coping Skills

In this simulation, the ambient agent observes several risks, such as; a high blood volume pressure, high alcohol level, and overdose pill intake. Based on this, the agent assesses that the person is facing a risk of relapse, subject to coping skills problem [12]. Therefore, the agent desires to give advice to improve coping skills, specifically to reduce anxiety and later to eliminate substance abuse are translated into intentions. Prior to this, the beliefs about the conditions must hold true. Figure 4 depicts the simulation trace of this condition.

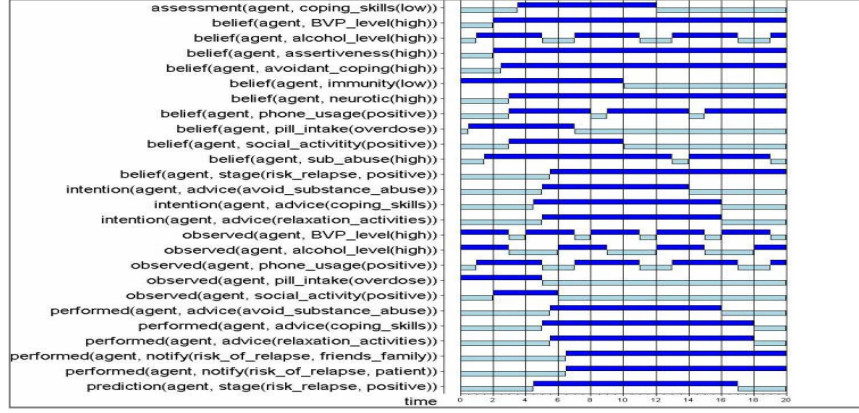


Fig. 4. Simulation Trace in Coping Skills Deficiencies.

Simulation # 3: Severe Risk Factors

The severe risk factors occur when all observed risk factor features show a positive contribution towards the future onset. Normally, seeking medical advice is the only best option [17]. When an ambient agent evaluates a patient is having all severe risk factors, the doctor or the therapist will be notified. The patient will receive a notification to seek for medical advice. The result of this condition is shown in Figure 5.

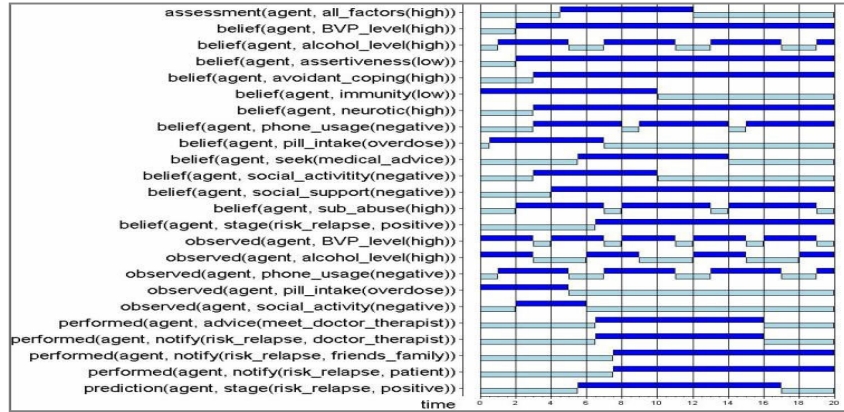


Fig. 5. Simulation Trace for All Severe Risk Factors.

5 Verification of The Model

This section deals with the verification of relevant dynamic properties of the cases considered in an ambient agent model. It is important to verify whether the

model produces results coherence with the literatures. It deals with building the model *right*. Several properties have been identified from related works in relapse management. The Temporal Trace Language (TTL) is used to perform an automated verification of specified properties against generated traces. This language allows formal specification and analysis of dynamic properties; it is either a qualitative or a quantitative representation [3]. TTL is designed on atoms, to represent the states, traces, and time properties. This relationship can be presented as a state(γ, t) $\models p$, means that state property p is true the state of trace at time point t [4]. It is also comparable to the *Holds*-predicate in the Situation Calculus. Based on that concept, dynamic properties can be formulated using a sorted first-order predicate logic (FOPL) approach.

VP1: Advice to avoid substance abuse during the risk of relapse

When a patient is believed to have a problem in substance abuse, prolong high neurotic level and vulnerable towards relapse (low in immunity) then the ambient agent provides advice to avoid substance abuse.

$$\begin{aligned}
& \forall \gamma: \text{TRACE}, t: \text{TIME} \\
& [\text{state}(\gamma, t) \models \text{belief}(\text{agent}, \text{sub_abuse}(\text{high})) \wedge \\
& \text{state}(\gamma, t) \models \text{belief}(\text{agent}, \text{neurotic}(\text{high})) \wedge \\
& \text{state}(\gamma, t) \models \text{belief}(\text{agent}, \text{immunity}(\text{low}))] \\
& \Rightarrow \exists t': \text{TIME} > t: \text{TIME} [\text{state}(\gamma, t') \models \text{performed}(\text{agent}, \text{advice}(\text{avoid_} \\
& \text{substance_abuse}))]
\end{aligned}$$

Substance abuse advice needs to be delivered if the patients are showing the risk of relapse, and with the combination of substance abuse problem, vulnerable to the onset, and prolong exposure to the anxiety [12]. It is vital since by prolong exposure towards substance abuse will increase the risk of future onset [8].

VP2: Warn for medical help if all risk conditions have been observed

When the doctor or therapist has been informed, the patient have already had all severe risk factors observed [8].

$$\begin{aligned}
& \forall \gamma: \text{TRACE}, t: \text{TIME} \\
& [\text{state}(\gamma, t) \models \text{performed}(\text{agent}, \text{notify}(\text{risk_relapse}, \text{doctor_therapist}))] \\
& \Rightarrow \exists t': \text{TIME} < t: \text{TIME} \\
& [\text{state}(\gamma, t') \models \text{belief}(\text{agent}, \text{sub_abuse}(\text{high})) \wedge \\
& \text{state}(\gamma, t') \models \text{belief}(\text{agent}, \text{neurotic}(\text{high})) \wedge \\
& \text{state}(\gamma, t') \models \text{belief}(\text{agent}, \text{immunity}(\text{low})) \wedge \\
& \text{state}(\gamma, t') \models \text{belief}(\text{agent}, \text{assertiveness}(\text{low})) \wedge \\
& \text{state}(\gamma, t') \models \text{belief}(\text{agent}, \text{social_support}(\text{negative}))]
\end{aligned}$$

VP3: Social support networks as a buffer for negative life events

When the ambient agent predicts a patient is having a risk in relapse then the ambient agent sends a notification message to related friends and family within the social support network members.

$$\begin{aligned} &\forall \gamma: \text{TRACE}, t: \text{TIME} \\ &\text{state}(\gamma, t) \models \text{prediction}(\text{agent}, \text{stage}(\text{risk_relapse}, \text{positive})) \\ &\Rightarrow \exists t': \text{TIME} > t: \text{TIME} [\text{state}(\gamma, t') \models \text{performed}(\text{agent}, \text{notify}(\text{risk_relapse}, \\ &\quad \text{friends_family}))] \end{aligned}$$

Friends and family within social support networks need to be informed if the patient is developing the risk of relapse in future. Ability to have social support is one of the crucial elements to reduce the risk of relapse [16] [17].

VP4: Relaxation training to reduce high comorbidity between anxiety and future onset

If the ambient agent observes a patient is having a high reading in blood volume pressure then the ambient agent provides advice on relaxation activities.

$$\begin{aligned} &\forall \gamma: \text{TRACE}, t: \text{TIME} \\ &\text{state}(\gamma, t) \models \text{observed}(\text{agent}, \text{BVP_level}(\text{high})) \\ &\Rightarrow \exists t': \text{TIME} > t: \text{TIME} [\text{state}(\gamma, t') \models \text{performed}(\text{agent}, \\ &\quad \text{advice}(\text{relaxation_activities}))] \end{aligned}$$

Anxiety can be reduced through a series of relaxation activities. By reducing the level of anxiety (neurotic), it will deplete the risk of having a relapse [17].

VP5: Involvement in several social activities to reduce the risk of relapse in the case of social withdrawal

When the ambient agent evaluates a patient is having social withdrawal and the ambient agent believes that a patient is having no social support then the ambient agent will provide advice to engage with suitable social activities.

$$\begin{aligned} &\forall \gamma: \text{TRACE}, t: \text{TIME} \\ &[\text{state}(\gamma, t) \models \text{assessment}(\text{agent}, \text{social_interaction}(\text{low})) \wedge \\ &\quad \text{state}(\gamma, t) \models \text{belief}(\text{agent}, \text{social_support}(\text{negative}))] \\ &\Rightarrow \exists t': \text{TIME} > t: \text{TIME} [\text{state}(\gamma, t') \models \text{performed}(\text{agent}, \\ &\quad \text{advice}(\text{social_activities}))] \end{aligned}$$

Deficits in social activities increase the chance of relapse. Positive social activities mitigate between stressful life events and onset [16].

6 Conclusion

In this paper, the model of an ambient agent to monitor relapse in depression is introduced. Within this ambient agent model, all-sub models are integrated to provide basic understanding for the agent to perform certain tasks (i.e; monitoring patient's conditions, evaluating the risk, or deciding actions) in order to sustain patients' wellbeing (by eliminating risk of developing another depression). The integration takes place by encapsulating domain model in all sub-models. A set of formal temporal properties are derived to allow intelligent reasoning to take place. From this formal model, several simulation runs were executed using LEADSTO language. The simulation results have been verified based on several properties using TTL environment. It was shown that the ambient agent model indeed through simulation is potentially be used to provide a support for patients. In addition, to conduct thorough evaluation and fine-tuning of the proposed model, future work will focus on generalizing the proposed model to an ambient agent based generic model for stress-risk evaluation and support in several related domains.

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Chapter 6

Design of an Intelligent Support Agent Model for People with a Cognitive Vulnerability

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Furthermore, part of this chapter appeared as:

Aziz, A.A., and Klein, M.C.A. (2011). Incorporating an Ambient Agent to Support People with a Cognitive Vulnerability. Book Chapter in *Human-Computer Interaction: The Agency Perspective*, Springer Verlag, (in press).

[2nd Witch]:
By the pricking of my thumbs,
Something wicked this way comes.
Open locks,
Whoever knocks!
[Macbeth]:
How now, you secret, black, and midnight hags!
What is't you do?

(William Shakespeare, Macbeth Act 4:scene 1)

Design of an Intelligent Support Agent Model for People with a Cognitive Vulnerability

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Abstract: This paper presents the design of an intelligent agent application aimed at supporting people with a cognitive vulnerability to prevent the onset of a depression. For this, a computational model of the cognitive processes around depression is used. The agent application uses the principles of Rational Emotive Behavioural Therapy. The effect of the application is studied using software simulation. The simulation shows that a person that responds to REBT therapy develops less cognitive vulnerability than people that are not supported.

Keywords: cognitive modeling, human-ambience agent, rational emotive behavioral therapy.

1 Introduction

Cognitive vulnerability is, from a broad perspective, a defect belief, or a set of structures that is persistently related to later emerging psychological problems. With in this context, it means that the cognitively vulnerable individuals could show negative cognitions, but that these cognitions are not accessible until they experience an activating event [1]. Several studies in affective disorders have pointed out that cognitive vulnerability is one of the precursors for future onset in unipolar depression [4]. Unipolar depression is a mood disorder characterized by a depressed mood, a lack of interest in activities normally enjoyed, fatigue, feelings of worthlessness and guilt, difficulty concentrating and thoughts of death and suicide [4]. If a person experiences the majority of these symptoms for longer than a two-week period then he may be diagnosed with major depressive disorder. Depression will also lead to a higher cognitive vulnerability. Normally, under a certain degree of stressors exposure, an individual with a history of depression will develop a negative cognitive content (cognitive distortion), associated with the past experiences [9]. When this has happened, the individual is vulnerable and in a high risk to develop future onsets.

The risk of future onset can be reduced through appropriate support from other members within the social support network. Social support network is made up of friends, family and peers. Some of them might be professionals and support individuals in very specific ways, or other people in this network might be acquaintances in people in contact with them every day [6]. Several studies have suggested that social support is capable to diminish stress through positive inferences, which will later restrain the formation of a cognitive vulnerability. However, some studies have shown that certain types of support provide contrasting effects. Rather than attenuating the negative effects from stressors, it will eventually amplify the individual's condition to get worse [8][9]. Therefore it is important for an individual with a high level of cognitive vulnerability to be supported by a specific mean of intervention in order to prevent future onset.

The goal of this research is to develop an intelligent agent application that can support people with a cognitive vulnerability to prevent the onset of a depression. In the past, intelligent agent technology has become an important means for increasing analysis, decision making ability and communication. To realise a supportive human agent application, it is required to integrate within the application a dynamical model of the human (domain model) that describes how an individual might experience cognitive vulnerability or could stay healthy. With that aim, a model of an ambient agent to support individuals with cognitive vulnerability is described, in which the domain model (cognitive model) is embedded [3]. The resulting integrative ambient agent is able to reason about the state of the human and the effect of possible actions. In case of vulnerability is predicted, the agent can provide to support by providing adequate remedies in an early stage. The aim of this paper is to present the basis of an intelligent ambient

inferential feedback (*MiF*) [7][9]. Both of these concepts are derived from the negative effect of received social support or non-supportive social support provision (*NsP*). As indicated in several previous works, inferential feedbacks provide one of the substantial factors towards the development of cognitive vulnerability (*CoV*) over time. By combining either one of these two factors together with situational cues, it leads to the formation of either cognitive depressogenic inferences (*CdI*) or positive attributional styles (*PtS*) [1].

Situational cues (*SiC*) refers to a concept that explains individuals' perception that highly influenced by cues from events (environment). Individuals under the influence of negative thought about themselves will tend to reflect these negative cognitions in response to the occurrence of stressors [7]. These later develop the conditions called "stress-reactive rumination". Stress reactive rumination (*SrR*) reflects a situation where individuals have trouble in accessing positive information, and further increase a negative bias towards future inference (maladaptive inference (*MalI*)) [14]. After a certain period, both conditions are related to the development of hopelessness (*HpS*). Hopelessness is defined by the expectation that desired outcome will not occur, or there is nothing one can do to make it right [9]. Prolong and previous exposure from hopelessness will lead to the development of cognitive depressogenic thought (*DyT*) and later influence the formation of cognitive vulnerability. The detailed discussion of the domain model can be found in [2].

3 Rational Emotive Behavioral Therapy

The intelligent agent application will provide support based on the ideas in the Rational Emotive Behavioural Therapy (REBT). This section will describe this therapy. In general, REBT is a comprehensive and active-directive psychotherapy which focuses on resolving emotional and behavioral problems and disturbances and enabling people have positive belief in their life [10]. One of the most important concepts in REBT is that humans, in most cases, do not merely get upset by unfortunate adversities, but also by how they construct their beliefs the events, themselves and other [11].

3.1 Important Concepts in REBT

REBT suggests that human beings defeat or disturb themselves in two main ways: (1) by holding irrational beliefs about their self (ego disturbance) or (2) by holding irrational beliefs about their emotional, social, or physical comfort (discomfort disturbance) [10]. To overcome these disturbances, REBT employs the 'ABC framework' to clarify the relationship between activating events and

individual's beliefs (A); individual's beliefs about them (B); and the cognitive, emotional or behavioural consequences of our beliefs (C) [10][11].

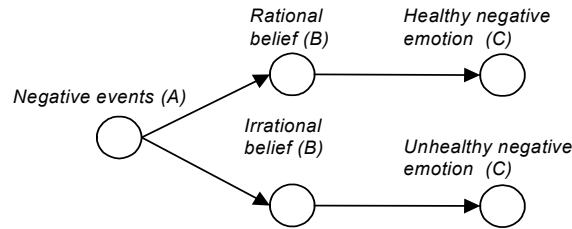


Fig. 2. Interactions in ABC Framework.

In practise, if a individual's evaluative B, belief about the A, activating event is dysfunctional, therefore the C, the emotional and behavioral consequence, is likely to be self-defeating and destructive. Alternatively, if a individual's evaluative B, belief is and constructive, then the emotional and behavioral consequence (C) is likely to be constructive. Fig. 2 depicts the effects of rational beliefs about negative events, which give rise to healthy negative emotions, and the effects of irrational beliefs about negative events, which lead to unhealthy negative emotion [10].

In addition the existing framework, REBT has also employed additional steps to provide prevention towards irrational belief. These steps are dispute irrational beliefs (D), and implement new effective thinking (E). Using this extended concept, individual will try to understand the role of their mediating, evaluative over unrealistic interpretations and assumptions in upset. Later, he or she often can learn to identify their irrational beliefs, challenge and question them. It will allow individual to distinguish them from unhealthy scenarios, and use more constructive and self-helping constructs.

3.2 Techniques

There are several techniques that can be adopted to alter irrational belief about the events, namely; cognitive, behavioural, and imaginary techniques. Cognitive techniques focus to detect irrational beliefs, to separate the rational from the irrational and to change one's way of thinking, while behavioural approaches are used to develop more effective ways of thinking by entering feared situations that individual would normally avoid. Imaginary techniques are designed to show that one's life and the world in general, continue after a feared or unwanted event has come and gone by visualizing the future outcomes of it. A complete description of these techniques is available in [10].

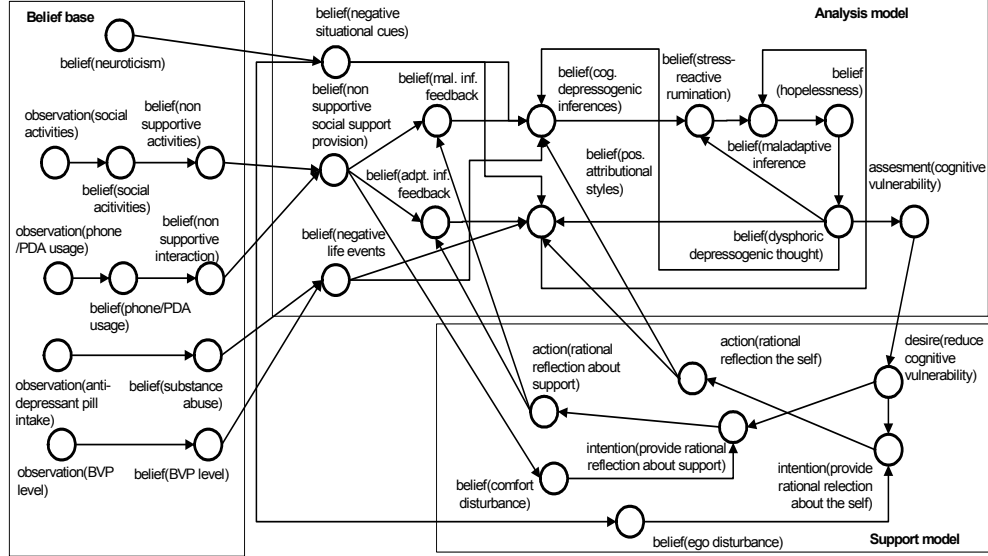


Fig.3. Detailed Interactions within an Ambient Agent.

4 Ambient Agent Model

In order to achieve an intelligent agent, an approach has been followed in which the dynamical domain model for depression is integrated in the model that describes the functioning of the ambient agent. By integrating the domain model, the ambient agent will be able to reason about the human and environmental processes. It is important to have such capabilities, since an ambient agent should be aware of human behaviours and states [3]. Through this mechanism, the agent will use this vital knowledge to provide related actions related to the predicted state of the human and the environment.

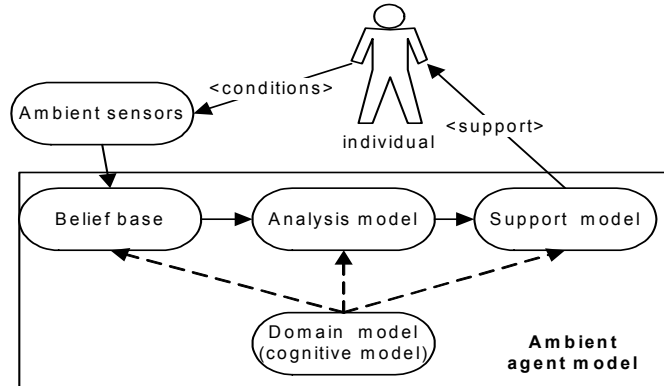


Fig. 4. Overview of the Ambient Agent Model.

In Fig. 4, the solid arrow indicates information exchange between processes, and the dotted arrow represents the integration process of the domain model within the ambient agent models. The detailed view of the model is shown in Fig. 3.

4.1 Belief Base

The main purpose of the belief base is to produce primary beliefs (basic and derived beliefs) from the ambient agent's observation about the individual's condition. Information about individual's condition can be obtained from several ambient sensors and devices. For example, Basic beliefs refer to beliefs related to the sensors (from the environment), while derived beliefs are based on derivations using the domain model. One of the advantages to have such concept is it allows future extension of the model. For example, if there is a new method (or sensors) can be used to measure belief in substance abuse, it is easily can be added as a basic belief for a new observation, and append it with the existing substance abuse belief. In addition, another belief model can make use this set of related beliefs without having to generate a new one.

Using pervasive and wearable technologies, such conditions can be observed through several ambient sensors and devices. For example, a medicine box that registers medication intake (MEMS) and passive alcohol sensor can used to observe potential substance abuse while a mobile phone / personal digital assistant (PDA), digital planner, and email interaction provide essential cues to monitor social interactions [3][12][13]. In addition to this, using blood pressure sensor provides important information to infer those individuals are experiencing potential stress [13]. These devices can potentially be integrated to support the real world application. However, a detailed discussion on these devices and signals is beyond the scope of this paper.

4.2 Analysis Model

One of the very important features to determine the level of cognitive vulnerability is the continuous assessment of changes in selected physiological and behavioural features within the individual. This assessment is highly related to the cognitive model encapsulated within the analysis model [3]. Using this cognitive model in the analysis model, the progression of the important features is analyzed. If the individual cognitive vulnerability level (from the assessment) is above the accepted threshold level for certain individual (*baseline threshold*), then the model will consider he/she is in the risk of experiencing an onset. By analyzing this condition, an agent will interfere this maladaptive progression by trigger desire to reduce an individual's cognitive vulnerability. This later will trigger the support model.

4.3 Support Model

For an individual at a high risk of cognitive vulnerability, necessary actions are needed to curb the onset stage. The ambient agent can use the results from analysis model to generate support actions for the individual. Information about beliefs in non-supportive social support provision and negative situational cues can be used to select an appropriate action. This important information will lead to the agent's beliefs either an individual is experiencing ego-disturbance (from belief in negative social cues) or comfort disturbance (non-supportive social support provision). For example, if the belief non-supportive social support provision holds true, then the agent perceives the individual is experiencing comfort disturbance.

By triggering belief in comfort disturbance, an agent generates an intention to support an individual. Later, by combining this intention with the desire to reduce an individual's cognitive vulnerability, an agent will provide a RBET intervention for both actions (to support action in rational reflection about support or about the self). As a result from this intervention process, it will curb the development of future irrational beliefs, and later provides effective new thinking on individual experienced conditions. In the domain model, the intervention effect from beliefs in comfort disturbance is calculated as follows.

$$MiF^+(t) = NsP(t).(1-RtO(t)) \quad (1)$$

$$AiF^+(t) = (1-(1-RtO(t)).NsP(t)) \quad (2)$$

where $MiF^+(t)$ and $AiF^+(t)$ represent individuals condition during intervention process for comfort disturbance. Moreover, the effect of intervention on beliefs in ego disturbance can be seen in these formulations.

$$PtS^+(t) = [\eta.AiF(t) + (1-\eta).(1-(SiC(t).DyT(t).NvT(t).(1-RtS(t))))].AiF(t) \quad (3)$$

$$CdI^+(t) = [\alpha.MiF(t) + (1-\alpha).SiC(t).DyT(t).MiF(t)].(1-RtS(t).NvT(t)) \quad (4)$$

where RtO and RtS functions represent the conditions to simulate the effects of intervention when any individual is experiencing distorted beliefs and receiving the support provided by an ambient agent. $PtS^+(t)$ and $CdI^+(t)$ computes the effect of this intervention in ego disturbance cases. These functions simulate three conditions; (1) an individual with a good skill to dispute the irrational belief, (2) an individual in a learning process and later acquired the skills, (3) an individual without any therapy skills and avoiding help.

5 Simulation Traces

The intervention as described in the previous section has been implemented in simulation environment. Using this simulation environment, we mimicked the intervention process to see its effect under several cases. Three scenarios are shown: an agent supports a individual with good skills in using cognitive techniques to the dispute distorted belief (**A**), an agent support with a individual who is new with RBET, learns the techniques, and later acquire the important skills to dispute the distorted belief (**B**), and a individual who refuse to accept help and incapable to acquire important skills to dispute the belief (**C**). These scenarios are studied under several negative events, namely; prolonged, repeated, and fluctuated events. In all cases, the temporal relations are initialized at 0.5. Corresponding to these settings, the level of severity (baseline to consider as a cognitive vulnerably condition) is set at 0.3, defining that any individuals scoring higher than 0.3 in their cognitive vulnerability level will be considered as experiencing difficulties and need help. In addition, these simulations used the following parameters settings: $t_{max}=1000$ (to represent a monitoring activity up to 42 days), $\Delta t=0.3$, all proportional and flexibility rates are assigned as 0.5 and 0.9 respectively. These settings were obtained from several systematic experiments to determine the most suitable parameter values in the model.

Prolonged Negative Events

During this simulation, each type of individual has been exposed to the highly extreme and constant negative events. In this simulation trace it shown that an individual *C* tends to experience cognitive vulnerable condition much faster compared to other people. Furthermore, the individual *C* also experienced persistent cognitive vulnerability throughout the development of negative events. As for the individual *B*, in the beginning of the simulation, individual *B* is experiencing the increasing effect towards cognitive vulnerability. However, after certain time point, note that an individual *B* shows a gradual decreasing level from potential cognitive vulnerability. Individual *A* is capable to lower the risk of cognitive vulnerability within the baseline boundary. The simulation results for these conditions are shown in Fig. 5.

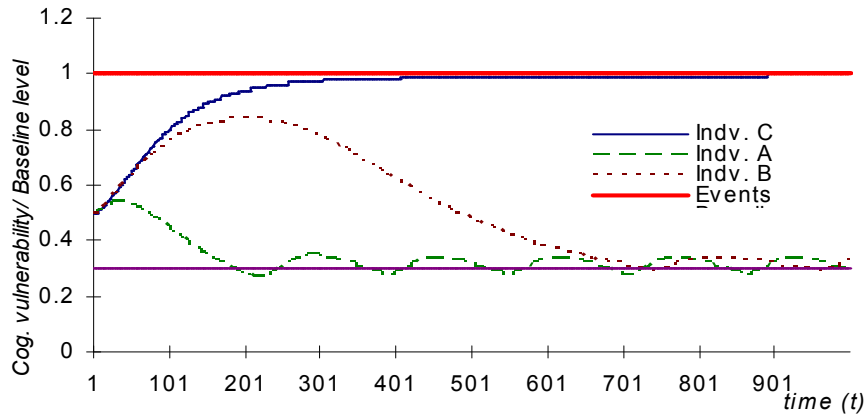


Fig. 5. Cognitive Vulnerability Level for Each Individual (prolonged stressors).

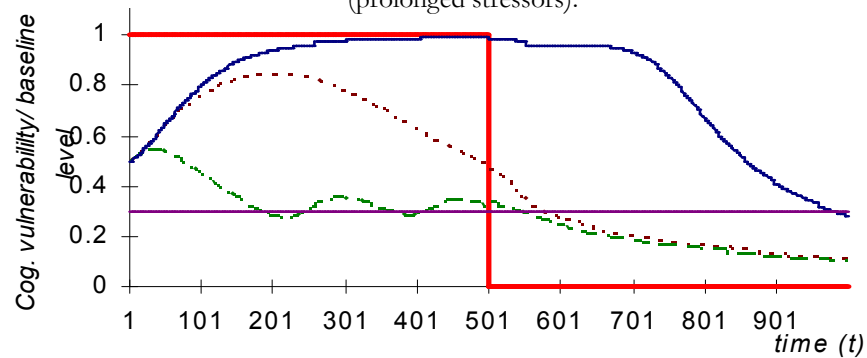


Fig. 6. Cognitive Vulnerability Level for Each Individual (fluctuated negative events).

Fluctuated Stressor Events

This simulation trace shows two types of periods, one with a very high constant and with a very low constant stressor event. These events occurred in a constant behaviour for a certain period of time (approximately within 20 days). Fig. 6 illustrates how each individual reacts with these conditions. Although all individuals show a full recovery state during the end of the simulation period, but for individual *C* it takes longer period to reach that particular state and it is only happens after the negative events (stressors) have diminished. Both individuals *A* and *B* show faster progression towards recovery compared to an individual *C*.

Repeated Stressor Events

During this simulation, all individuals are exposed to repeated negative events, that later will decline gradually. These conditions represent an individual is experiencing an extreme stream of stressor events, with a rapid alteration between each corresponding event.

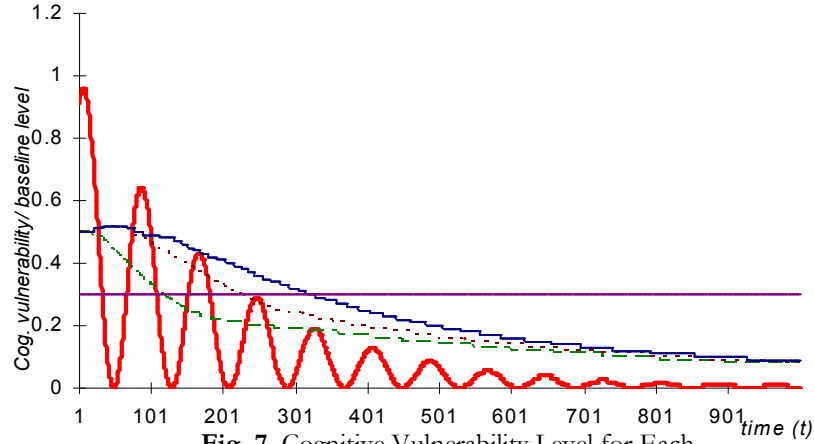


Fig. 7. Cognitive Vulnerability Level for Each Individual (repeated negative events).

As can be seen from Fig. 7, when the stressors decrease, all individuals show decreasing patterns in their cognitive vulnerability. However, an individual C has shown a slow decline progression towards a full recovery stage.

6 Automated Verification

This section deals with the verification of relevant dynamic properties of the cases considered in the ambient agent model. It is important to verify whether the model produces results that are coherent with the literature and appropriate to help the patient. The Temporal Trace Language (TTL) is used to perform an automated verification of specified properties against generated traces. This language allows formal specification and analysis of dynamic properties using a combination of a qualitative and a quantitative representation [5].

VP1 : Individuals with Good Skills in RBET will Reduce the Risk of Future Cognitive Vulnerability

When an individual capable to perform good skills in RBET, then the individual will unlikely to develop further cognitive vulnerability in future.

$$\begin{aligned} \text{VP1} \equiv & \forall \gamma: \text{TRACE}, t, t': \text{TIME}, R1, K1, V1, V2, \text{MIN_LEVEL_SELF}, \\ & \text{MIN_LEVEL_SUPPORT:REAL}, X: \text{AGENT} \\ & [\text{state}(\gamma, t) \models \text{rational_reflection_self}(X, R1) \ \& \\ & R1 \geq \text{MIN_LEVEL_SELF} \ \& \\ & \text{state}(\gamma, t) \models \text{rational_reflection_support}(X, K1) \ \& \end{aligned}$$

$$K1 \geq \text{MIN_LEVEL_SUPPORT} \ \& \ \text{state}(\gamma, t) \models \text{cognitive_vulnerability} \\ (X, V1) \ \& \ V1 > 0] \Rightarrow \exists t': \text{TIME} > t: \text{TIME} \ [\text{state}(\gamma, t') \models \\ \text{cognitive_vulnerability}(X, V2) \ \& \ V1 < V2]$$

In some simulation traces, a condition was added to the antecedent of the formal property, namely $t=200$ so the property only checked at the given time step. In general, this property can be used to verify future condition of an individual if the individual capable to infer positive (rational) interpretations of experienced events throughout time.

VP2: Monotonic Increase of Cognitive Vulnerability for Individual without Good Skills and Experiencing Prolonged Stressors

When an individual is incapable to perform RBET, then the individual will prone to develop further cognitive vulnerability in future.

$$\text{VP2} \equiv \forall \gamma: \text{TRACE}, t, t': \text{TIME}, D1, D2, F1, F2: \text{REAL}, X: \text{AGENT} \\ [\text{state}(\gamma, t) \models \text{stressors}(X, D1) \ \& \\ \text{state}(\gamma, t') \models \text{stressors}(X, D2) \ \& \\ \text{state}(\gamma, t) \models \text{cognitive_vulnerability}(X, F1) \ \& \\ \text{state}(\gamma, t') \models \text{cognitive_vulnerability}(X, F2) \ \& \ t' > t \ \& \\ D2 \geq D1] \Rightarrow F2 \geq F1$$

By checking property VP2, one can verify whether any individual (without good skills in RBET) increase monotonically in his/her cognitive vulnerability after experiencing prolonged stressors.

VP3: Monotonic Decrease of Cognitive Vulnerability for Any Individual When Stressors are Reduced

When an individual is experiencing lesser stressors throughout time, then the individual will reduce the level of cognitive vulnerability in future.

$$\text{VP3} \equiv \forall \gamma: \text{TRACE}, t, t': \text{TIME}, D1, D2, F1, F2: \text{REAL}, X: \text{AGENT} \\ [\text{state}(\gamma, t) \models \text{stressors}(X, D1) \ \& \\ \text{state}(\gamma, t') \models \text{stressors}(X, D2) \ \& \\ \text{state}(\gamma, t) \models \text{cognitive_vulnerability}(X, F1) \ \& \\ \text{state}(\gamma, t') \models \text{cognitive_vulnerability}(X, F2) \ \& \ t' > t \ \& \\ D2 \leq D1] \Rightarrow F2 \leq F1$$

Property VP3 can be used to verify individual's condition when negative events (stressors) are decreasing throughout time.

7 Conclusion

Depression is a serious mood disorder that influences the life of the patient enormously. Unfortunately, the disease has a high rate of relapse. The occurrence of depression and the rate of relapse are probably related to the

cognitive vulnerability of the patients. In this paper a cognitive model has been described that specifies the dynamics of the mood and thought according to the theory of cognitive vulnerability. This model is used as the basic component of an intelligent agent application aimed at supporting people to prevent the onset of a depression. The application uses the model to analyze patients and detect risk full situations.

When such situations are detected, an intervention is taking place following the principles of Rational Emotive Behavioural Therapy (based on changing the underlying thoughts). A software simulation has been implemented to study the effect of the application. In these simulations, three cases are compared: a not cognitive-vulnerable person, a person that responds to REBT therapy, and a person that does not respond to the therapy. Finally, using several generated traces, the model has been verified using a number of important properties in the literature.

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Chapter 7

Computational Modeling of Therapies Related to Cognitive Vulnerability and Coping

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"Happiness can be found in the darkest of times, if one remembers to turn on the light."

(Albus P. W. B. Dumbledore, Harry Potter and the Prisoner of Azkaban)

Computational Modeling of Therapies Related to Cognitive Vulnerability and Coping

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Abstract: Due to recent research, the neurobiological elements behind mental disorders such as depression become more and more clear. This paper presents an integrated computational model based on neurobiological insights and psychological theories. The model is used to analyse the effect of existing psychological treatments. The simulation experiments give an insight in the interaction between different cognitive components in mental disorders and illustrates why different treatments can have different effects for people with different genetic dispositions.

Keywords: computational modeling in therapy, cognitive models in cognitive vulnerability and coping, simulation.

1 Introduction

Cognitive vulnerability and coping are important elements of the explanation of mental disorders, such as depression [4]. More and more, the neurobiological elements behind these disorders become clear. With the increased understanding of these mechanisms, also the possibilities increase to create adequate computational models of mental diseases. Such models can contribute to a better understanding of the mechanism, form a basis for e-mental health applications and can be used for the analysis of the effect of (combinations of) therapies.

In this paper, an integrated computational model is described that uses knowledge about cognitive vulnerability and coping. The model is a combination of two previously developed models and describes the dynamics of the cognitive states over time. A more detailed discussion for both domain models can be found in [1][2]. The integrated model is extended with a sub-model that describes two specific psychological treatments, i.e. Acceptance and Commitment Therapy (ACT), and Rational Emotive Behavioural Therapy (RBET). The combined model is used to analyse the effect of these treatments by performing simulation experiments.

The remainder of the paper is organized as follows. In Section 2, some recent insights about the neurobiological background of mental disorders are reviewed. Based on this, the subsequent section presents the integrated dynamic model of cognitive states related to mental disorders. In Section 4, a sub-model is introduced that describes the treatments. Both are used as basis for simulation experiments and their analysis in Sections 5 and 6. Section 7 concludes the paper.

2 Biological Perspectives in Cognitive Vulnerability and Coping

Recent decades have witnessed an explosion of research on neurobiological aspects in mental health. It has become an important approach to unlock the mystery of mental disorders. In the neurobiological area important relationships between cognitive, behaviours, affective, and neurobiological underpinnings can be grounded. For example, negative appraisals of stressors lead to the release of cortisol and increase the vulnerability for depression. Cortisol has a vital role in shutting down the sympathetic function and to suppress the hypothalamus pituitary-adrenocortical (HPA) activities by a negative feedback mechanism on the hippocampus, amygdala, and pituitary and plays an important role to restore normal hormone levels [6]. Therefore, any dysregulation of the HPA implies that cortisol is inhibiting the peripheral nervous system to maintain physiological homeostasis. Another important concept to explain cognitive vulnerability is the cumulative burden borne by a brain and body adapting to stress (*allostatic load*) [9]. From this stand, it is predicted that the individual with active HPA activities

and locus coeruleus-norepinephrine system (a nucleus in the brainstem involved with physiological responses to stress) will have the highest risk for allostatic load, and increased the risk of cognitive vulnerability towards stress. Reconsolidation is another biological process that relevant to cognitive vulnerability to the effects of extreme stress. It explains how old and reactivated memories can be integrated into an ongoing perceptual and emotional experience and becomes part of new memory [6]. Moreover, several clinical studies indicate that the consolidation process in amygdala and hippocampus are sensitive to disruption upon reactivation of several protein synthesis inhibitors.

In the coping styles literature it is shown that the magnitude of neuro-endocrine stress response depends on whether the stressor is appraised as threatening or as challenging. Threat appraisals are more strongly associated with prolonged higher reactive levels of cortisol (increased reactivity), while challenge appraisals are characterized by rapid cortisol responses with quick recovery [5][9]. Additionally, although the effective use of emotional-focused coping may dampen the endocrine stress response by not getting overwhelmed by negative affects, it will only work on the short time, where it is related to the sustained levels of cortisol and sympathetic activation. In the long term, the sustained activation will result in physiological and affective problems. Coping is also related to the several active brain regions, where evidence is accumulating that coping is a part of the overall set of executive functions that regulated by the prefrontal cortex [6]. For example, problem focused coping strategies were related to the inhibitory control activities, and emotional-focused coping shown a poorer inhibition result [5].

Specifically, from both cognitive vulnerability and coping concepts, we can see several common aspects that each concept has important interplay with one to another. This interplay can be seen through the activities in HPA, cortisol, and also several brain regions activation. In a cognitive model perspective, this biological interaction can abstractly be seen in several important theories to explain cognitive vulnerability and coping process, namely; (1) Extended Hopelessness Theory of Depression and (2) Cognitive Motivational Relational Theory [8][13].

3 A Model for Cognitive Vulnerability and Coping

The model used in this paper is a combination of two previously developed models to explain the dynamics in human vulnerability towards stress and coping skill strategies. The detailed discussion for both domain models can be found in [1][2]. Figure 1 depicts the interaction of these two models.

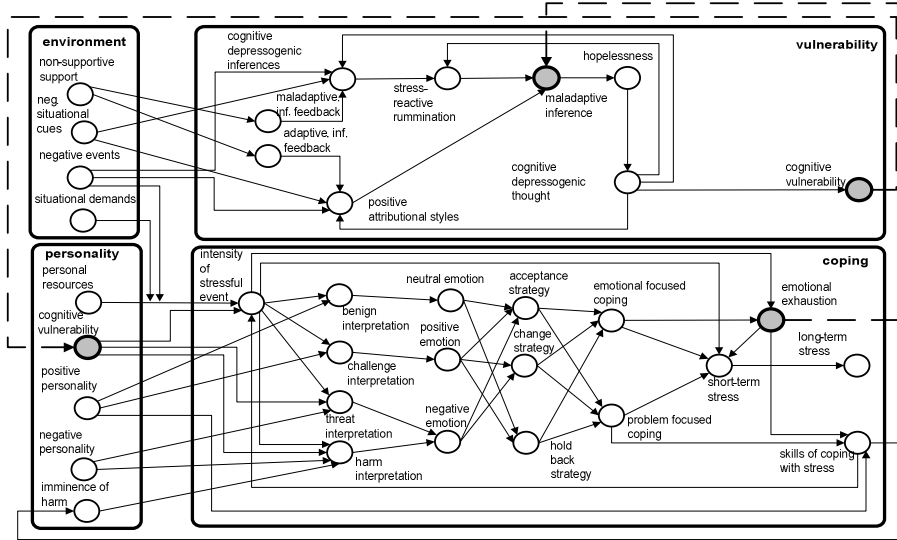


Fig. 1. The Integrated Domain Model of Cognitive Vulnerability and Coping.

3.1 Concepts in Cognitive Vulnerability & Coping

The cognitive vulnerability model has been developed based on the *Extended Hopelessness Theory of Depression*. In this theory, people who exhibit a negative inferential style, in which they describe, negative events (*NeV*) to stable and will affect many aspects of life will most likely to infer themselves as fundamentally useless [7]. One of the important concepts from this theory is the analysis on how social support mitigates a risk of relapse (positive feedback (*AiF*)), and indirectly escalates the risk of relapse (maladaptive inferential feedback (*MiF*)), related to negative reflection of received support (*NsP*) [7]. By combining either one of these two factors together with situational cues, it leads to the formation of either cognitive depressogenic inferences (*CdI*) or positive attributional styles (*PlS*) [5]. Situational cues (*SiC*) refers to a concept that explains individuals' perception that highly influenced by cues from events (environment) [11]. These later develop where individuals have trouble in accessing positive information (stress-reactive rumination (*SrR*)), and further increase a negative bias towards future inference (maladaptive inference (*MdI*)) [7][11]. After a certain period, both conditions are related to the development of hopelessness (*HpS*), and later will lead to the development of cognitive depressogenic thought (*CdT*) and cognitive vulnerability (*CoV*) [8].

In a coping model, the *Cognitive Motivational Relational Theory* (CMRT) is used [13]. Several factors such as *situational demands* (*SiD*), *personal resources* (*PrA*), and *negative events* play important roles to influence perception towards incoming stressors (*IsE*) [4]. Normally, a person appraises two types of appraisals; the

primary and the secondary. The primary appraisal is made to evaluate person's well being. Firstly, the situation can be appraised either as harm/loss (*HrM*), threatening (*TbT*), challenging (*ChL*) or benign (*BgN*). Later this process will determine individuals' emotion perception; negative (*NgE*), positive (*PsE*) or neutral (*NuE*) emotion [13]. Negative emotion is related to perceiving *harm* and *threat*, neutral emotion is corresponded to *benign* condition and positive emotion is attributed to perceiving *challenge*. Secondly, a person evaluates whether he or she has the resources to deal with the stressors. It is commonly related to the emotional attribution, where a positive and neutral emotion results in *acceptance* (*AcP*) and *change* (*ChG*), while the negative emotion triggers *holdback* (*HdB*) [2]. Later, it will lead to the *problem* (*PrF*) and *emotion-focused coping* (*EmF*). A problem-focused coping is associated with rational efforts to get the problem solved, while emotion-focused coping strategies entail efforts to regulate the emotional consequences of stressful events [14]. All these strategies can be proven useful, but many individuals feel that in a long run, emotion focused coping is associated with outcomes that people found unsatisfactory (emotional exhaustion in coping (*ExH*)) that later will develop short (*SS*) and term stress (*LS*). Problem focused coping is associated with satisfactory outcomes (improved coping skills (*SS*)) [13].

4 Modeling Therapies for Cognitive Vulnerability and Coping

In this section, it shown how the influences of selected therapies (Acceptance and Commitment (ACT), and Rational Emotive Behavioural (RBET) Therapy) are modelled in the extended model presented in Section 3. First, important concepts in evaluating cognitive vulnerability and coping will be discussed, followed by ACT and RBET.

4.1 Important Concepts in Evaluating Cognitive Vulnerability and Coping

One of the very imperative features to verify the level of related conditions such as cognitive vulnerability and long-term stress is the continuous evaluation of changes in selected physiological and behavioural features within the individual. Using the domain model, the development of the vital features is analyzed and predicted. These features provide the dynamic relationships in the model. For example, the observable feature in a long-term stress can be related from the accumulation of short-term stress states and so forth [2]. There are several important concepts need to be measured, namely; long-term stress (*LS*), emotional exhaustion (*ExH*), cognitive vulnerability (*CoV*), and coping skills (*SS*). These concepts are calculated as follows:

$$LIS(t+\Delta t) = LIS(t) + \beta_i [\text{Pos}(SIS(t) - LIS(t)) \cdot (1 - LIS(t)) - \text{Pos}(-(SIS(t) - LIS(t))) \cdot LIS(t)] \cdot \Delta t \quad (1)$$

$$ExH(t+\Delta t) = ExH(t) + \psi_e [\text{Pos}((IsE(t) - ExH(t)) \cdot (1 - ExH(t))) - \text{Pos}(-(IsE(t) - ExH(t)) \cdot ExH(t))] \cdot EmF(t) \cdot \Delta t \quad (2)$$

$$ScS(t+\Delta t) = ScS(t) + \phi_e [\text{Pos}(ExH(t) - ScS(t)) \cdot (1 - ScS(t)) - \text{Pos}(-(ExH(t) - ScS(t)) \cdot ScS(t))] \cdot PrA(t) \cdot \Delta t \quad (3)$$

$$CoV(t+\Delta t) = CoV(t) + v_e [\text{Pos}(CdT(t) - CoV(t)) \cdot (1 - CoV(t)) - \text{Pos}(-(CdT(t) - CoV(t)) \cdot ScS(t))] \cdot \Delta t \quad (4)$$

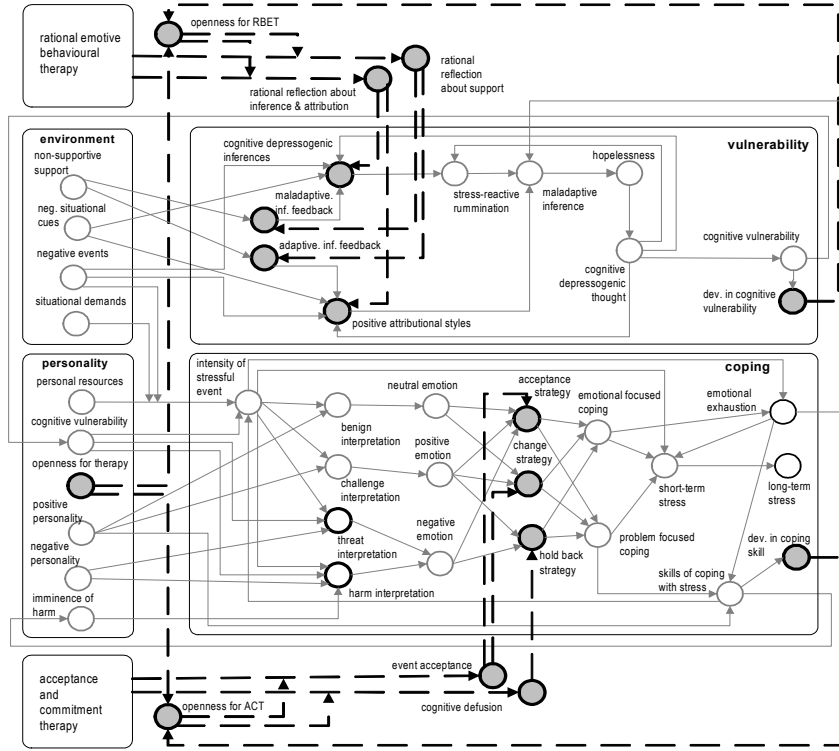


Fig. 2. The Integrated Model in an Agent Based Therapy for ACT and RBET.

The rates of change for all temporal relationships are determined by flexibility parameters β_i , ψ_e , ϕ_e , and v_e respectively. The operator Pos for the positive part is defined by $\text{Pos}(x) = (x + |x|)/2$, or alternatively; $\text{Pos}(x) = x$ if $x \geq 0$ and 0 else.

4.2 Intervention for Acceptance and Commitment, and Rational Emotive Behavioural Therapy

In this section it is shown how the influences of two types of therapies are modeled in the extended model presented in Section 3. First, acceptance and commitment therapy will be discussed, followed by rational behavioural emotive therapy. Figure 2 shows an overview of the relevant states and dynamics in the model. The states that are depicted in grey represent states have been added and corresponded to model the points of impacts in therapies. The same holds for the dashed lines. In this model, openness for therapy (OfT) is a state indicating how open the individual is for therapy, which is made specific for each particular influence of therapy, namely openness for ACT (OfA), and openness for RBET (OfR). Furthermore, the development in coping skills (DeC) and cognitive vulnerability (DeV) will influence openness for ACT, and RBET respectively.

$$OfA(t) = OfT(t).DeC(t) \quad (5)$$

$$OfR(t) = OfT(t).DeV(t) \quad (6)$$

Acceptance and Commitment Therapy: Fundamentally, ACT emphasizes such processes as mindfulness, acceptance, and values in helping individuals overcome obstacles in their lives. There are three core processes in ACT, however; only two processes (*cognitive defusion* and *acceptance*) are discussed here to change individual's coping preference [12]. Cognitive defusion (CgD) (means “detach from unhelpful thoughts and worries” and event acceptance (EvA) deals with reducing the effort to avoid certain situations (where discerning between thoughts, feelings, and experiences is a prominent focus) [12]. The effects from these processes will allow more acceptance and change strategies to take place in coping. This can be expressed as follows:

$$AcP(t) = \zeta_a [\gamma_a PsE(t) + (1 - \gamma_a) NuE(t)] \cdot [1 - ((1 - IeA(t)) NgE(t))] + (1 - \zeta_a) IeA(t) \quad (7)$$

$$CbG(t) = \nu_g [PsE(t) \cdot (1 - ((1 - IcD(t)) NgE(t))] + (1 - \nu_g) IcD(t) \quad (8)$$

$$HdB(t) = \zeta_b [(1 - PsE(t)) \cdot (1 - IcD(t))] + (1 - \zeta_b) (1 - IcD(t)) \quad (9)$$

where, $IeA(t) = EvA(t)$, $OfA(t)$, and $IcD(t) = CgD(t).OfA(t)$

Rational Behavioural Emotive Therapy: REBT suggests that human beings defeat themselves in two main ways: (1) by holding irrational beliefs about their self (ego disturbance), (2) by holding irrational beliefs about their emotional, or social comfort (discomfort disturbance) [3]. Therefore the RBET identifies those problematic ideas, and replaces them with more rational perspectives (such as positive perspectives to self attribution (RtS), and provided support (RtO)) [3]. As a result from this intervention process, it will restrain the progress of future

irrational beliefs, and later provides effective new thinking on individual experienced conditions. The intervention effects are calculated as follows.

$$MiF(t) = NsP(t).(1-ItO(t)) \quad (10)$$

$$AiF(t) = (1-((1-ItO(t)).NsP(t))) \quad (11)$$

$$PtS(t) = [\eta_p.AiF(t) + (1-\eta_p).(1-(SiC(t).DyT(t).NeV(t). (1-ItS(t))))].AiF(t) \quad (12)$$

$$Cdl(t) = [\alpha_s.MiF(t) + (1-\alpha_s).SiC(t).DyT(t).MiF(t)].(1-ItS(t)).NeV(t) \quad (13)$$

where, $ItO(t) = RtO(t).OfR(t)$ and $ItS(t) = RtS(t).OfR(t)$

Here parameters, $\zeta_a, \gamma_a, \psi_a, \zeta_b, \alpha$ and ψ_b represent the proportional factor for all respective instantaneous variables.

5 Simulation Results

In this section, simulation results are presented. The intervention as described in the previous section has been implemented in simulation environment. To this end, software to generate simulation traces was developed in Matlab. Using this simulation environment, we mimicked the intervention process to see its effect under several cases. Three fictional individuals are studied with divergent values for personality attributes. These values are chosen to depict the different influences of the therapies on different types of individuals. Table 1 shows the values for the most important variables of the model for each individual.

Table 1. Personality Attributes for the Simulation Experiments.

Personality Attributes \ Individuals	<i>A</i>	<i>B</i>	<i>C</i>
<i>Positive Personality</i>	0.2	0.5	0.8
<i>Personal Resources</i>	0.1	0.3	0.7
<i>Openness for Therapy</i>	0.7	0.7	0.7
<i>Situational Demands, Situational Cues, Negative Events</i>	0.9	0.9	0.9

In all cases, the long term stress, emotional exhaustion, cognitive vulnerability, and coping skill value are initialized at 0.3. These simulations used the following parameters settings: $t_{max}=1000$ (to represent a monitoring activity up to 42 days), $\Delta t=0.3$, all proportional and flexibility rates are assigned as 0.5 and 0.3 respectively. These settings were obtained from several systematic experiments to determine the most suitable parameter values in the model. . For the sake of brevity, this section will only discuss the results of individual *A*. First, the simulation without any form therapy is shown (Figure 3(a)).

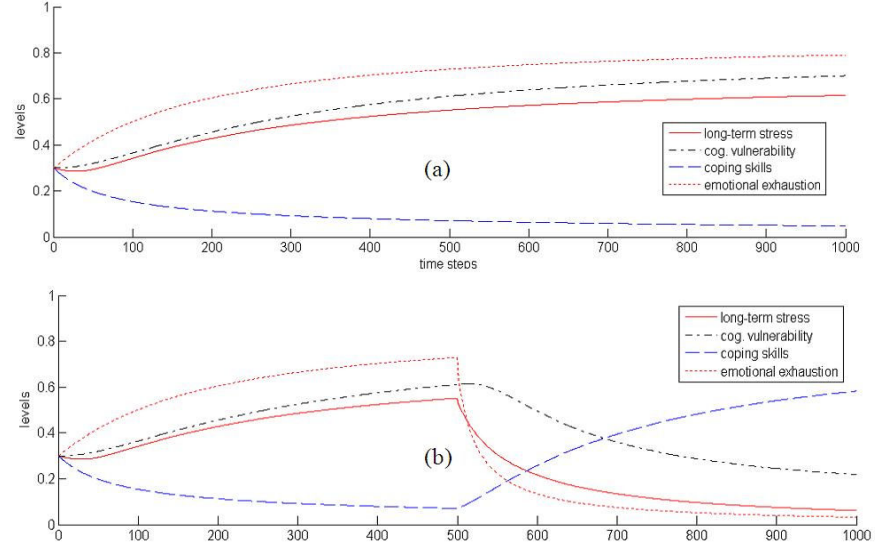


Fig. 3. Individual type \mathcal{A} (a) Without Following Any Therapy, (b) following the ACT therapy.

The individual experiences very negative events during monitoring period. Since the individual is susceptible towards stress (low coping skills and highly vulnerable), a long-term stress follows [4][8]. Later it will lead an individual to fall into depression. For the second experiment; individual \mathcal{A} is receiving the ACT therapy (Figure 3(b)). For this case, it can be seen that the long-term stress, cognitive vulnerability, and emotional exhaustion are decreased. In addition to this, it increases individual's ability to cope as well [13]. For the RBET, the same types of experiments have been conducted. Figure 4 shows the result from following this therapy.

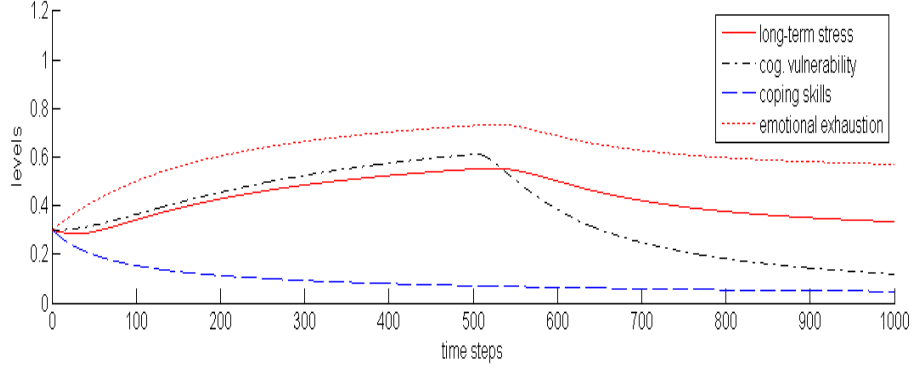


Fig. 4. Individual type \mathcal{A} following the RBET therapy.

In this case, individual \mathcal{A} experiences slow recovery in long-term stress and emotional exhaustion, and a rapid recovery from cognitive vulnerability. Another variability is used for the experiment is assigning different openness level for individual \mathcal{A} . If the openness towards therapy is increased, the individual \mathcal{A} recovers more quickly compares to lower openness values. In the case of individual \mathcal{B} , for all three conditions, individual \mathcal{B} recovers faster compares to individual \mathcal{A} . Meanwhile individual \mathcal{C} receives a very low negative effect from the incoming stressors, and manages to recover even without receiving any therapy [4]. In addition to these experiments, when an individual \mathcal{A} follows both therapies in the same time, it shows a slightly faster recovery than following only a single therapy.

6 Automated Verification

In order to verify whether the model indeed generates results that adherence to psychological literatures, a set of properties have been identified from related literatures. Therefore, these properties will answer whether the model produces results that are coherent with the literature and appropriate to help people with cognitive vulnerability and coping problems, To allow the verification process to take place, these properties have been specified in a language called Temporal Trace Language (TTL). TTL is built on atoms referring to states of the world, time points, and traces. This relationship can be presented as a state(γ , t , output(R)) $\models p$, means that state property p is true at the output of role R in the state of trace γ at time point t [16]. It is also comparable to the *Holds*-predicate in the Situation Calculus. Based on that concept, dynamic properties can be formulated using a sorted predicate logic approach, by manipulating quantifiers over time and traces and first-order logical connectives such as \neg , \wedge , \vee , \Rightarrow , \forall ,

and \exists . A number of simulations including the ones described in Section 4 have been used as basis for the verification and were confirmed.

VP1: Effectiveness of ACT in problem focused coping

After a person has followed the ACT therapy for some times, the problem focused coping skills have improved.

$$\begin{aligned} \text{VP1} \equiv & \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME}, \forall R1, R2, D1, D2: \text{REAL} \\ & [\text{state}(\gamma, t1) \mid = \text{has_value}(\text{ACT_therapy}, R1) \ \& \\ & \text{state}(\gamma, t2) \mid = \text{has_value}(\text{ACT_therapy}, R2) \ \& \\ & \text{state}(\gamma, t1) \mid = \text{has_value}(\text{problem_focused_coping}, D1) \ \& \\ & \text{state}(\gamma, t2) \mid = \text{has_value}(\text{problem_focused_coping}, D2) \ \& \\ & t1 < t2 \ \& \ R2 > R1] \Rightarrow D2 \geq D1 \end{aligned}$$

VP2: Problem focused coping helps a person to recover faster than emotional focused coping

A problem focused coping skill is a better option compares to an emotional focused coping skill in a long-term recovery.

$$\begin{aligned} \text{VP2} \equiv & \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME}, \forall M1, M2, D1, D2: \text{REAL} \\ & [\text{state}(\gamma, t1) \mid = \text{has_value}(\text{problem_focused_coping}, M1) \ \& \\ & \text{state}(\gamma, t1) \mid = \text{has_value}(\text{emotional_focused_coping}, M2) \ \& \\ & \text{state}(\gamma, t1) \mid = \text{has_value}(\text{long_term_stress}, L1) \ \& \\ & \text{state}(\gamma, t2) \mid = \text{has_value}(\text{long_term_stress}, L2) \ \& \\ & t1 < t2 \ \& \ M1 > M2] \Rightarrow L1 > L2 \end{aligned}$$

VP3: Effect of cognitive vulnerability towards long term stress

Reducing the cognitive vulnerability level will reduce the risk of future long term stress.

$$\begin{aligned} \text{VP3} \equiv & \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME}, \forall F1, F2, H1, H2, d: \text{REAL} \\ & [\text{state}(\gamma, t1) \mid = \text{has_value}(\text{cog_vulnerability}, F1) \ \& \\ & \text{state}(\gamma, t1) \mid = \text{has_value}(\text{cog_vulnerability}, F2) \ \& \\ & \text{state}(\gamma, t1) \mid = \text{has_value}(\text{long_term_stress}, H1) \ \& \\ & \text{state}(\gamma, t2) \mid = \text{has_value}(\text{long_term_stress}, H2) \ \& \\ & t2 \geq t1 + d \ \& \ F1 < F2] \Rightarrow H2 < H1 \end{aligned}$$

VP4: ACT results in higher recovery in stress than RBET

After a person has followed ACT, the long-term stress is lower than after following RBET.

$$\begin{aligned} \text{VP4} \equiv & \forall \gamma1, \gamma2: \text{TRACE}, \forall t1, t2: \text{TIME}, \forall M1, M2, L1, L2, d: \text{REAL} \\ & [\text{state}(\gamma1, t1) \mid = \text{has_value}(\text{ACT_therapy}, M1) \ \& \\ & \text{state}(\gamma2, t1) \mid = \text{has_value}(\text{RBET_therapy}, M2) \ \& \\ & \text{state}(\gamma1, t2) \mid = \text{has_value}(\text{long_term_stress}, L1) \ \& \end{aligned}$$

$$\text{state}(\gamma_2, t_2) \models \text{has_value}(\text{long_term_stress}, L_2) \ \& \ t_2 \geq t_1 + d \ \& \ M_1 = 1 \ \& \ M_2 = 1 \Rightarrow L_1 < L_2$$

7 Discussion

Because of the increased insights in the neurobiological basis of mental disorders, it is possible to make more detailed models of these disorders. In this paper, an integrated model that relates cognitive vulnerability and coping strategies has been presented. The model has been described in a computational software package, which allows performing simulation experiments that describe the development of the different factors over time. The simulation experiments that have been presented give an insight in the interaction between different cognitive components in mental disorders. It also shows that ACT therapy is more effective for improving coping skills, while RBET therapy has the largest effect on the factors related to cognitive vulnerability. Due to the interaction of the concepts, both therapies will contribute to less stress. The experiments suggest that there is a only limited added value in combining both therapies.

The model presented in this paper is based on neurobiological and psychological theoretical knowledge. Further research is required to investigate to what extent the simulations give an adequate description of actual development in persons with mental disorders. Based on questionnaires or continuous assessments using modern ICT tools such as mobile phones, the development of mood and stress of actual people could be monitored. The outcome of these experiments can be used to validate and tune the presented model. The validated models can be used as basis for e-mental health applications that guide patients and suggest the best interventions by predicting their effect.

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Part IV

Computational Models for Depressed Persons and their Social Support Networks

Chapter 8

An Agent Model for a Human's Social Support Network Tie Preference during Unipolar Depression

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“It's important to our friends to believe that we are unreservedly frank with them, and important to the friendship that we are not.”

(Mignon McLaughlin, The Neurotic's Notebook)

An Agent Model for a Human's Social Support Network Tie Preference during Unipolar Depression

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Abstract: Seeking support from their environment is important for people suffering from a depression. People usually have different social networks to which they are attached with different ties. In this paper, a computational model is presented that describes the selection of network members for seeking support based on the strength of the tie to people in the network and personal characteristics. The model has been implemented in a simulation environment. Simulations of different scenarios show that specific personality traits and environmental settings indeed lead to a pattern of social disengagement or a preference for strong or weak tie support. A mathematical analysis proves that such equilibria are indeed a consequence of the model.

Keywords: depression, social support networks preference, simulation model.

1 Introduction

Depression is one of the most prevalent psychological disorders, reflected by a strong mood involving sadness, despair, or hopelessness lasts for weeks, months, or even longer [3]. More often, it causes pain and suffering not only to those who have a disorder, but also to those who care about them. People who are experiencing the development of depression seek help from people in their environment. There are patterns in help-seeking behaviour among depressed people, especially with history of onset. It is often possible to relate such conditions with individual's ability to choose which people to rely on [1][14]. The groups of people around a person that can provide help are called "social support networks". Generally, the social support network is referred to a social network's provision towards psychological or material resources deliberated to promote an individual's ability to cope with stressors [5][6]. This kind of a social construct provides a stress-buffering mechanism, which aims to eliminate or to reduce harmful effects of stressful experiences by providing less-negative interpretations of unpleasant events, and suitable coping styles [5][16]. Most of the social support interaction is a social interpersonal process that mainly focused on the reciprocal exchange of information. The outcome of the interaction is broadly categorized as to improved individual health. It is highly dependent on the specific circumstances, but it is primarily related to previous social experiences and types of relationships within members in the social support networks (support provider).

An important mechanism behind the support-seeking behaviour is the selection of social support networks based on the strength of the tie with the people in the network. Social support ties selection answers the question of individual's preferences towards certain individuals within the social support networks [16]. This paper presents a model that describes this selection process. It provides a human agent model that simulates social support ties preferences, which specifically relates to several individual attributes, with respect to a person's reaction to stressful events. There are many situations where can be useful when implemented in a software agent. For example, it could provide the basis for a personal agent that suggests social support network members to contact according to an individual's preferences during the formation of stress or recurrence in depression. The present paper is organized as follows; Section 2 describes theoretical concepts of social support tie preference. From this perspective, a formal model is designed and formulated (Section 3). Later, in Section 4, several simulation traces are presented to illustrate how this model satisfies the expected outcomes in social support ties preference. In Section 5, a detailed mathematical analysis is performed, in order to identify equilibria in the model. Finally, Section 6 concludes the paper.

2 Social Support Ties Preference

Over the past several decades, researchers from a variety of domains have focused on the relationship between social support processes and mental health. For example, researchers in a communication domain have contributed to the development of theories and understanding of social support provisions, by providing foundations on inter-relation on supportive messages, positive appraisals, and coping behaviors such as Weak Tie/Strong Tie Support Network Theory [2][10].

2.1 Weak/Strong Tie Support Theory

The Weak Tie/Strong Tie Support Network Theory explains how individual coordinates the support-seeking process while managing the relational concerns and individual needs [12]. Strong tie is a relationship typically between individuals in a close personal network. Close associates such as family, spouses, and friends are frequently acknowledged as a strong tie support provider. While, a weak tie is typically occurs among individuals who communicate on relatively frequent basis, but do not consider them as close acquaintances [1][6]. The individual's need for support influences the selection of support providers from relationship [7][16]. For example, several studies have shown that many individuals with long-term perspectives (*future goal orientation*) having difficulty to attain appropriate informational support from close friends or acquaintances since they feel this group of people has limited skills or knowledge towards individuals' problems [2]. However, if the individuals' intention to seek for the emotional support (*emotional goal orientation*) is higher, then they tend to choose a weak tie support over strong tie [9][11]. Individual characteristics are highly related to personality traits (*neurotic*), individual's risk in stress (vulnerability / *risk of mental illness*), and expected support (*expected amount of support*) from social support members [8][15].

In addition, predilection to seek support appears to be rooted in individual's support orientation (either emotion or future orientation goal), closeness in relationship (*intimate relational history*) and support member expected obligation (*role obligation*) [14][16]. This combination explains the condition where one may oblige to provide support for those who are close, but may feel it a burden if a loved one needs a great support and it can lead to conflict (*relational complication*). Without further motion to overcome this, it will later increase the risk of relational erosion (*social disengagement*) through a series of prolonged dissatisfaction in relationships (*relational dissatisfaction*) [5][10]. As a result, individual tends to avoid from seeking support, which is one of the outcomes in depression [12][14]. Another characteristic that involves in selecting social support ties is interpersonal trust (*trust in support*). When individual is ensured

about the predictability of the social support tie (especially in a weak tie network), he or she will develop a secure sense of attachment towards trusting others [6][16]. This trust concept reflects that trusting individuals beyond the strong tie support network is more likely to view a support seeking behaviour as an appropriate course of action regardless of the potential risks in trust [16]. It is one of the main precursors to seek and receive help [5]. Within the support provision, it is also equally important to assume that support providers always to be reliably available and willing to give support during challenging time.

3 A Multi-Agent Model for Social Support Networks

This section discusses the details of the dynamic model. Several works discussed in the previous section heavily motivates the characteristics of the proposed model.

3.1 Formalizing the Human-Agent Model Relationship

In this model, three main components are interacting to each other to simulate support-seeking behaviours. These components are grouped as; inter-personal and individual attributes, support preference generation, relationship erosion process, stress component, and support feedbacks. Initially, negative events acts as a stimulus trigger the stress component. This stress condition is amplified by individual attributes such as risk of stress (or risk of mental illness) and neurotic personality and accumulates to develop a long-term stress condition [3]. With the existence of short-term stress, the support preference generation is generated, pertinent to the individual and inter-personal attributes [6]. Similar information also will be channeled to the social erosion component. Social erosion component acts to diminish individual's ability in seeking help [14]. After the social support tie preference is selected, then the support feedbacks are received. To simplify the interaction, this model assumes all support feedbacks received provide a positive effect towards human agent well-being (stress-buffering mechanism) [5]. Finally, the social support feedback also will be used to reduce the relationship erosion effect within individual [2][15]. The details of this model are shown in Fig. 1.

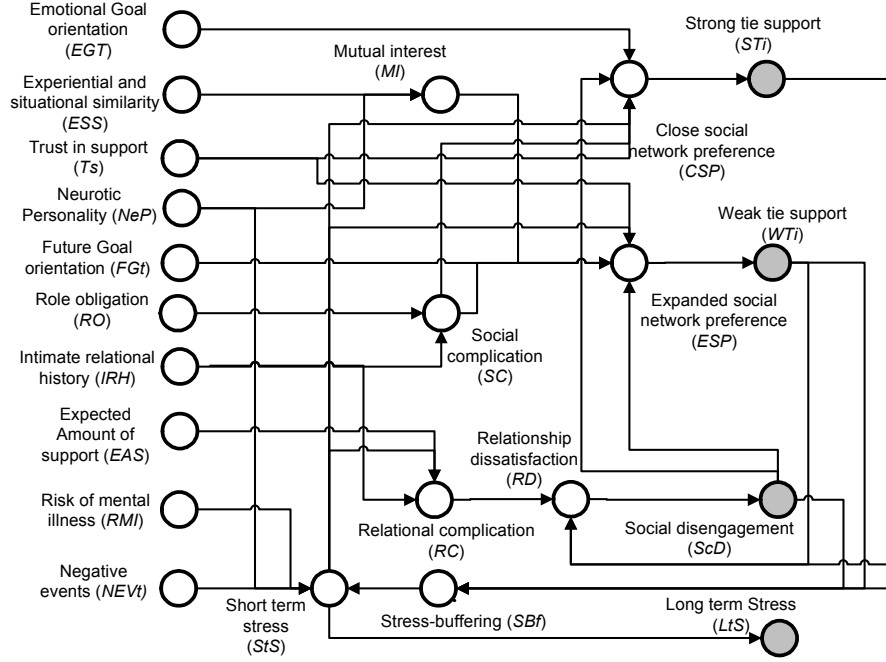


Fig. 1. Global Relationships of Variables Involved in the Social Support Ties Preference.

To support the design of the model (as shown in Fig. 1), the dynamic model was developed. This model involves a number of instantaneous and temporal relations, which will be discussed in greater detailed below.

3.2 Instantaneous Relations

The instantaneous relations are derived from several formulae, namely; mutual interest (MI), social complication (SC), relationship complication (RC), relationship dissatisfaction (RD), short-term stress (StS), stress-buffering (SBf), close social network preference (CSP), and expended social network preference (ESP). These relations were designed as given by the following formulae.

$$MI(t) = \alpha_{mi}.ESS(t).(1-NeP(t)) \quad (1)$$

Mutual interest is calculated using the combination of experiential situational similarity (ESS) and positive personality (contrary to neurotic personality (NeP)). It means, having a positive personality and a common experience will foster a better mutual interest engagement. Parameter α_{mi} represents the contribution factor pertinent to individual personality.

$$SC(t) = \beta_{sc}.IRH(t).RO(t) \quad (2)$$

The effect of social complication is determined by multiplying the value of intimate relational history (*IRH*) and role obligation (*RO*). This relation explains the aspect of support personal resources expectation. The proportional factor for social complication is determined by β_{sc} .

$$RC(t) = \gamma_r.EAS(t).IRH(t) + (1-\gamma_r).[RMI(t).StS(t)] \quad (3)$$

Relational complication is measured using the proportional contribution (determined by γ_r) of the expected support (*EAS*) and intimate relational history (*IRH*) with the risk of stress (*RMI*) and short-term stress (*StS*).

$$RD(t) = \eta_{rd}.RC(t).(1-STi(t)).(1-WTi(t)) \quad (4)$$

Relational dissatisfaction is determined by η_{rd} times relational complication when no support is given (neither from strong tie (*STi*) nor weak tie (*WTi*)).

$$StS(t) = [\psi_{sts}.NEVt(t) + (1-\psi_{sts}).RMI(t).NeP(t)].(1-SBf(t)) \quad (5)$$

The level of short-term stress depends on the relation between the stress buffering (*SBf*) level and the proportion contribution of negative events (*NEVt*), risk of stress (*RMI*), and neurotic personality (*NeP*). Here, ψ_{sts} represents the proportional contribution factor for this relation. If $\psi_{sts} \rightarrow 1$, then external factor (negative event) will contribute a greater role towards the formation of short-term stress.

$$SBf(t) = \phi_{sbf}[\eta_{sbf}.STi(t) + (1-\eta_{sbf}).WTi(t)].(1-ScD(t)) \quad (6)$$

Stress buffering is calculated using the presence of support and the level of social disengagement (*ScD*). Note that, η_{sbf} regulates the level of support tie contribution. In this relation, a high social disengagement level ($SBf \rightarrow 1$) will cause stress buffering becomes less effective.

$$CSP(t) = \gamma_{csp}[\beta_{csp}.EGt(t) + (1-\beta_{csp}).Ts(t).(1-SC(t))].(1-ScD(t)).StS(t) \quad (7)$$

The level of close social network preference depends to the level of emotional goal orientation (*EGt*), short-term stress, trust in support (*Ts*), social complication and social disengagement. The amount of preference will increase if there is a presence of short-term stress and low social disengagement. Parameter β_{csp} regulates the contribution of preference selection attributes, while γ_{csp} represents the contribution factor in overall relation.

$$ESP(t) = \psi_{esp} [\eta_{esp} FG(t) + (1 - \eta_{esp}) Ts(t) MI(t) (1 - SC(t)) (1 - ScD(t)) StS(t)] \quad (8)$$

Close social network preference is calculated using the level of future goal orientation (FG), short-term stress, trust in support, mutual interest, social complication and social disengagement. Similar to the condition in (7), the presence of social complication and social disengagement decreases the expanded social network preference level. Similar case also occur when $StS \rightarrow 0$. ψ_{esp} represents the proportion factor and η_{esp} provides a proportional contribution factor in expanded social network preference attributes.

3.3 Temporal Relations

In addition, there are four temporal relationships are involved, namely strong-tie preference (STi), weak-tie preference (WTi), social disengagement (ScD), and long-term stress (LtS). The rate of change for all temporal relationships are determined by flexibility parameters, ϕ_{sti} , ϕ_{wti} , η_{scd} and β_{lt} respectively.

$$STi(t + \Delta t) = STi(t) + \phi_{sti} (1 - STi(t)) (CSP(t) - \psi_{sti} STi(t)) (STi(t)) \Delta t \quad (9)$$

Here, strong-tie preference builds or reduces over time. When CSP is higher than the previous strong-tie preference multiplied with the contribution factor, ψ_{sti} , then the strong-tie preference increases. Otherwise, it decreases depending on its previous level and contribution factor. This condition also can be used to explain for the rest of all temporal relations, according to their respective parameters and attributes. It should be noted that the change process is measured in a time interval between t and $t + \Delta t$. In addition, the social disengagement is referring to the concept of not-seeking support or withdrawal from having one.

$$WTi(t + \Delta t) = WTi(t) + \phi_{wti} (1 - WTi(t)) (ESP(t) - \eta_{wti} WTi(t)) (WTi(t)) \Delta t \quad (10)$$

$$ScD(t + \Delta t) = ScD(t) + \eta_{scd} (1 - ScD(t)) (RD(t) - \psi_{scd} ScD(t)) (ScD(t)) \Delta t \quad (11)$$

$$LtS(t + \Delta t) = LtS(t) + \beta_{lt} (1 - LtS(t)) (StS(t) - \xi_{lt} LtS(t)) (LtS(t)) \Delta t \quad (12)$$

Using all defined formulas, a simulator has been developed for experimentation purposes; specifically to explore interesting patterns and traces that explains the behaviour of the human agent model. This simulator is developed under a visual programming platform. It allows a graphical user interface for experimental and parameters settings purposes. All simulation results will be generated and stored in spreadsheets for further analysis.

4 Simulation Results

A number of simulations have been performed, intended to explore some interesting patterns in human-agent social support-tie preference behaviours. With several variations of the individual and inter-personal attributes, some expected patterns can be found. In this paper, there are three individual conditions will be dealt under two different stressors events (prolonged and fluctuated events). Table 1 outlines the values of these individual profiles.

Table 1. Individuals Profiles.

Individuals	Profiles (<i>EGt, FGt, ESS, NeP, IRH, EAS, RMI, RO</i>)
A	<i>0.8, 0.1, 0.1, 0.5, 0.9, 0.8, 0.5, 0.8</i>
B	<i>0.1, 0.8, 0.9, 0.5, 0.1, 0.8, 0.5, 0.1</i>
C	<i>0.4, 0.6, 0.6, 0.1, 0.3, 0.3, 0.3, 0.1</i>

The duration of the simulation is up to 1000 time points, with these simulation parameters settings;

$$\begin{aligned}
\Delta t &= 0.3, \varphi_{sti} = \phi_{nti} = \eta_{sdi} \beta_{lis} = 0.2, \\
\psi_{sts} &= \eta_{sbj} = \beta_{esp} = \eta_{esp} = 0.5, \\
\alpha_{mi} &= \beta_{sc} = \gamma_{re} = \eta_{nd} = \varphi_{sb}, \\
j &= \gamma_{cp} = \psi_{esp} = 0.8.
\end{aligned}$$

These experimental results will be discussed in detail below.

Case # 1: Exposure in Prolonged Stressor Events

During this simulation, all types of individuals have been exposed to an extreme case of stressor events. This kind of pattern is comparable to the prolonged stressors throughout a lifetime.

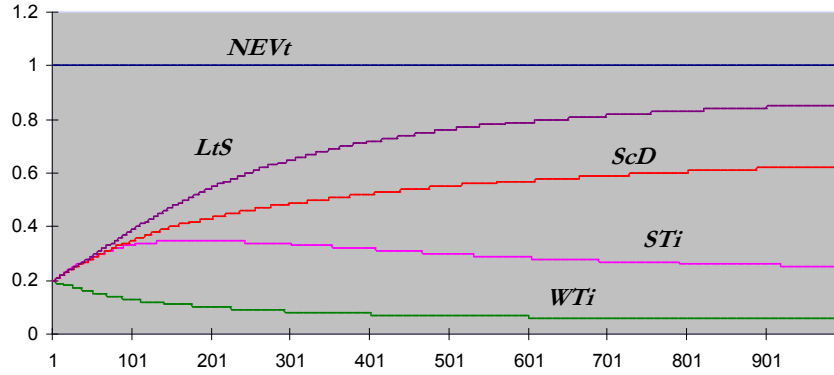


Fig. 2. Support Preferences for Individual A.

For the first individual (individual A) (according to Fig. 2), tends to disengage from seeking support after long period of exposure in negative events. This characteristic is in line with the findings reported in [5]. It explains the conflict of overburden from overwhelming expected supports, and new role obligations towards individual with such characteristic and negative events. This individual is prone to the risk in developing potential onset. Similar event was also simulated for individual B (with tendency in a weak tie support, highly neurotic personality, too high-expectation in support, and high risk in mental illness). This individual has a preference over a weak tie support over strong tie. As is shown in Fig. 3, this individual lesser long-term stress effect, and capable to main its support ties. However, without a proper action, this individual tends to gradually developing a potential risk of long-term stress that will lead to the recurrence in depression.

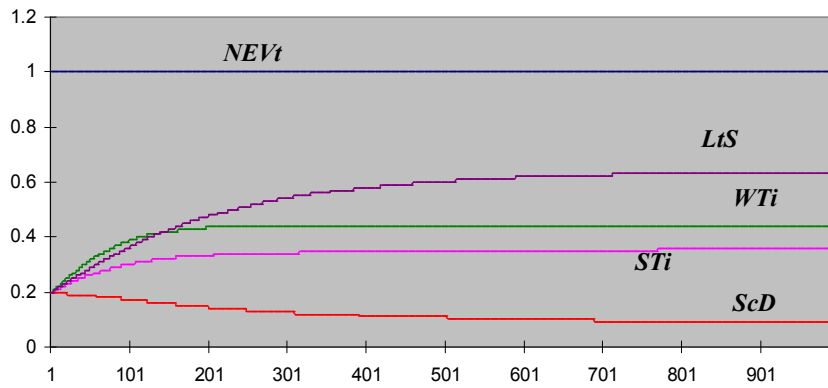


Fig. 3. Support Preferences for Individual B.

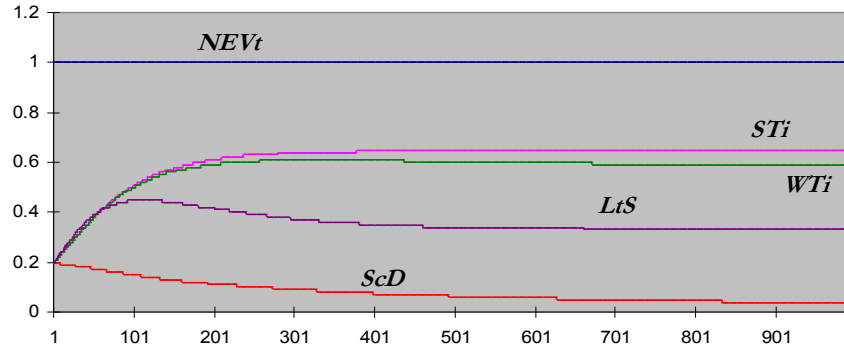


Fig. 4. Support Preferences for Individual C.

As can be seen from Fig 4, individual C, with normal personality attributes (less neurotic, moderate expectation, balance support seeking attributes) indicates a gradual reduction in a long-term stress. This individual tends to be stable in seeking and receiving support from both social network ties.

Case # 2: Exposure Fluctuated Stressor Events

In this experiment, two kinds of stressors were introduced. The first stressor is one with a very high constant, and is followed by the second one, with a very low constant stressor event.

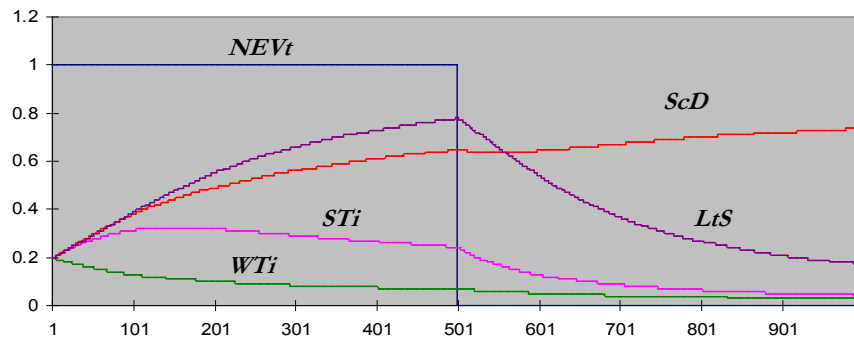


Fig. 5. Support Preferences for Individual A.

From Fig. 5 it can be seen that individual A gets to develop a social withdrawal pattern, even without the presence of negative events. Moreover, such individual attributes affect that individual's perception towards support and social interaction.

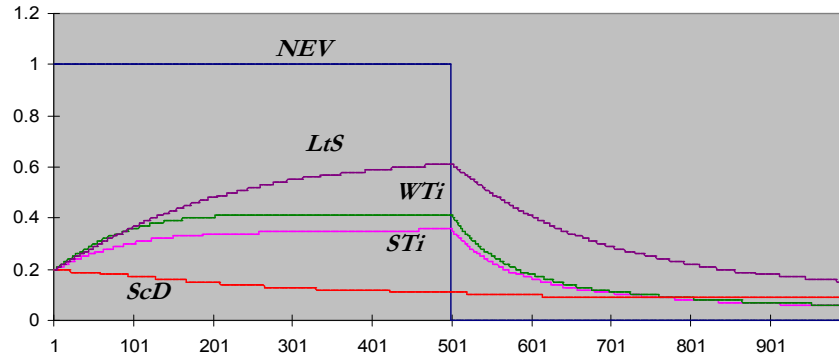


Fig. 6. Support Preferences for Individual B.

Meanwhile, as in shown in Fig. 6, individual B has much lower long term stress effect, and develop a positive feedback towards a better wellbeing. Note that both support ties preference levels are suddenly dropped. The reason of this condition is support-seeking behaviour only occur when individual is facing negative events. In this connection, it is worth noting this result is based from the concept that social support network tie is coherent with the stress buffering effect, rather a typical social interaction during a normal daily life [2][6].

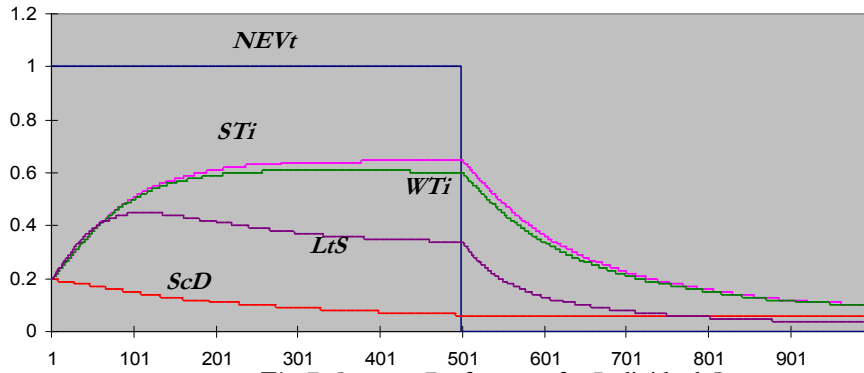


Fig.7. Support Preferences for Individual C.

As for individual C (Fig. 7), it shows a better buffering effect compared to both individuals. In addition, it can be seen both support tie preferences are decreasing rapidly after the absent of negative events. This precursor has already been mentioned during previous discussion.

5 Formal Analysis

One of the aspects that can be addressed by a mathematical analysis is which types of stable situations are possible. To this end equations for equilibria can be determined from the model equations. This can be done to assume constant values for all variables (also the ones that are used as inputs). Then in all of the equations the reference to time t can be left out, and in addition the differential equations can be simplified by cancelling, for example $STi(t+\Delta t)$ against $STi(t)$. This leads to the following equations:

$$MI = \alpha_{mi}.ESS.(1-NeP) \quad (13)$$

$$SC = \beta_{sc}.IRH.RO \quad (14)$$

$$RC = \gamma_{rc}.EAS.IRH + (1-\gamma_{rc}).[RMI.StS] \quad (15)$$

$$RD = \eta_{rd}.RC.(1-STi).(1-WTi) \quad (16)$$

$$StS = [\psi_{stS}.NEVt + (1-\psi_{stS}).RMI.NeP].(1-SBf) \quad (17)$$

$$SBf = \phi_{sbj}.[\eta_{sbj}.STi + (1-\eta_{sbj}).WTi].(1-ScD) \quad (18)$$

$$CSP = \gamma_{csp}[\beta_{csp}.EGt + (1-\beta_{csp}).Ts.(1-SC)].(1-ScD).StS \quad (19)$$

$$ESP = \psi_{esp}[\eta_{esp}.EGt + (1-\eta_{esp}).Ts.MI.(1-SC)].(1-ScD).StS \quad (20)$$

$$\phi_{sti}.(1-STi).(CSP - \psi_{sti}.STi).(STi) = 0 \quad (21)$$

$$\phi_{wti}.(1-WTi).(ESP - \eta_{wti}.WTi).(WTi) = 0 \quad (22)$$

$$\eta_{scd}.(1-ScD).(RD - \psi_{scd}.ScD).(ScD) = 0 \quad (23)$$

$$\beta_{lls}.(1-LLS).(StS - \xi_{lls}.LLS).(LLS) = 0 \quad (24)$$

Assuming the parameters ϕ_{sti} , ϕ_{wti} , η_{scd} , β_{lls} nonzero, from the equations (21) to (24), the following cases can be distinguished:

$$STi = 1 \quad \text{or} \quad CSP = \psi_{sti}.STi \quad \text{or} \quad STi = 0$$

$$WTi = 1 \quad \text{or} \quad ESP = \eta_{wti}.WTi \quad \text{or} \quad WTi = 0$$

$$ScD = 1 \quad \text{or} \quad RD = \psi_{scd}.ScD \quad \text{or} \quad ScD = 0$$

$$LLS = 1 \quad \text{or} \quad StS = \xi_{lls}.LLS \quad \text{or} \quad LLS = 0$$

Theoretically spoken this amounts to $3^4 = 81$ possible equilibria. Note that the last equation (24) is isolated from the others, and therefore can be handled separately. But for the other three still 27 possibilities remain. Also given the other equations (13) to (20) with the 10 input variables, this makes it hard to come up with a complete classification of equilibria. However for some typical cases the analysis can be pursued further.

Case $STi = 1$ $WTi = 1$ $ScD = 0$:

For this case, by equation (18) it follows that

$$SBf = 1$$

and hence by equation (17)

$$StS = 0$$

Moreover, from (16) it follows that

$$RD = 0$$

From this the other variables can be determined; from (13) to (15) it follows:

$$MI = \alpha_{mi}.ESS.(1-NeP),$$

$$SC = \beta_{sc}.IRH.RO,$$

$$RC = \gamma_{rc}.EAS.IRH$$

Finally, from (19) and (20) it follows

$$CSP = 0, ESP = 0$$

Case $ScD = 1$:

For this case, by equation (18), (19) and (20) it follows that

$$SBf = 0, CSP = 0, ESP = 0,$$

Moreover, by equation (17) it follows

$$StS = \psi_{sts}.NEVt + (1-\psi_{sts}).RMI.NeP$$

and from (16) it follows that

$$RD = \eta_{rd}.RC.(1-STi).(1-WTi)$$

which is 0 in case one of STi or WTi is 1. Finally the other variables can be determined; from (13) to (15) it follows:

$$MI = \alpha_{mi}.ESS.(1-NeP),$$

$$SC = \beta_{sc}.IRH.RO,$$

$$\begin{aligned} RC &= \gamma_{rc}.EAS.IRH + (1-\gamma_{rc}).[RMI.StS] \\ &= \gamma_{rc}.EAS.IRH + (1-\gamma_{rc}).[RMI. \psi_{sts}.NEVt + \\ &\quad (1-\psi_{sts}).RMI.NeP] \end{aligned}$$

Case $StS = 0$:

From equation (17) it follows that this is equivalent to:

$$[\psi_{sts}.NEVt + (1-\psi_{sts}).RMI.NeP].(1-SBf) = 0$$

This can (only) occur in the following subcases:

$$[\psi_{sts}.NEVt + (1-\psi_{sts}).RMI.NeP] = 0 \quad \text{or} \quad SBf = 1$$

Assuming ψ_{sts} nonzero and not 1, this is equivalent to:

$$\begin{aligned} NEVt &= 0 \quad \text{and} \quad RMI = 0 \quad \text{or} \quad NEVt = 0 \quad \text{and} \quad NeP = 0 \\ \text{or} \quad SBf &= 1 \end{aligned}$$

By equation (18) the latter case $SBf = 1$ is equivalent to

$$\varphi_{sbf}[\eta_{sbf}.STi + (1-\eta_{sbf}).WTi].(1-ScD) = 1$$

Assuming η_{sbf} nonzero and not 1, this is equivalent to

$$\varphi_{sbf} = 1, STi = 1, WTi = 1, ScD = 0$$

So for this subcase, the case $STi=1$ $WTi=1$ $ScD=0$ applies. Therefore from the analysis above addressing the latter case it follows

$$\begin{aligned} RD &= 0, \\ MI &= \alpha_{mi}.ESS.(1-NeP), \\ SC &= \beta_{sc}.IRH.RO, \\ RC &= \gamma_{rc}.EAS.IRH, \\ CSP &= 0, ESP = 0 \end{aligned}$$

Case $StS = 1$

For this case, from equation (17) it follows that the case is equivalent to:

$$[\psi_{sts}.NEVt + (1-\psi_{sts}).RMI.NeP].(1-SBf) = 1$$

Assuming ψ_{sts} nonzero and not 1, this is equivalent to:

$$NEVt = 1, RMI = 1, NeP = 1, SBf = 0$$

By equation (18) $SBf = 0$ is equivalent to

$$\phi_{sbf}[\eta_{sbf}.STi + (1-\eta_{sbf}).WTi].(1-ScD) = 0$$

Assuming ϕ_{sbf} and η_{sbf} nonzero and η_{sbf} not 1, this is equivalent to:

$$STi = 0 \text{ and } WTi = 0, \text{ or } ScD = 1$$

The latter sub case was already addressed above. Continuing with the former subcase $STi = 0$ and $WTi = 0$ for this subcase from equation (16) it follows that

$$RD = \eta_{rd}.RC$$

6 Discussion

In this paper a computational model is presented that describes the selection of support networks for patients suffering from a depression. Based on the Weak Tie/Strong Tie Support Network Theory, the personality characteristics of a person are related to the preference for a specific support network and the overall willingness of seeking support. The effect of the support on the stress buffer and indirectly on the mood of the patient is also described. Together, these elements provide a dynamic model that can be used to simulate the development of a depression in a person and the role and support from the social environment. The model has been implemented in different scenarios that represent specific personality traits and environmental settings indeed lead to a pattern of social disengagement or a preference for strong or weak tie support. A mathematical analysis proves that such equilibria are indeed a consequence of the model. This model can be used as the basis for a personal software agent that supports a person suffering from depression [3] [4]. Such a system could monitor the mood of the patient and suggest, based on knowledge about the personality traits of the patient and a simulation of the benefit of the support from people

form a specific network, a person to contact to seek help from. In addition, the model could be used by a therapist for analyzing the role of specific personality traits in the development of the depression and the use of the social network of the patient. This analysis could possibly be used as basis for interventions.

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Chapter 9

Modelling Dynamics of Social Support Networks for Mutual Support in Coping with Stress

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“‘Ohana’ means family - no one gets left behind, and no one is ever forgotten.”

(Lilo, Lilo and Stitch)

Modelling Dynamics of Social Support Networks for Mutual Support in Coping with Stress

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Abstract: This paper presents a computational multi-agent model of support receipt and provision to cope during stressful event within social support networks. The underlying agent model covers support seeking behavior and support provision behaviour. The multi-agent model can be used to understand human interaction and social support within networks, when facing stress. Simulation experiments under different negative events and personality attributes for both support receipt and provision pointed out that the model is able to produce realistic behavior to explain conditions for coping with long term stress by provided mutual support. In addition, by a mathematical analysis, the possible equilibria of the model have been determine

Keywords: social support networks, strong and weak ties, stressors, support recipient and provision, multi-agent simulation.

1 Introduction

Persons differ in their vulnerability for stress. To cope with stress, the social ties of the person are an important factor [2][5]. Such ties are the basis of social networks or communities within which support is given from one person to the other and vice versa. Examples of such social networks are patient communities for persons suffering from a long or forever lasting and stressful disease. Providing and receiving social support within such a network is an intra and interpersonal process, with as a major effect that it improves the quality of life of the members of the social network. This fundamental form of human functioning is an important aspect of our lives. Research shows that in the event of stress a social support network is able to influence individuals' wellbeing and act as a buffer for the impact of negative events. In recent years, social support with particularly the perception of support seeking and availability (provision), has well documented positive effects on both physical and psychological health. The explication of relationship between support seeking and provision has been studied intensively to explain this relationship. For example, simply knowing that someone is available to support can be comforting and capable to alleviate the effect of negative events [4][8]. More general social support helps its recipients to escalate self-confidence and overcome the risk of stress [5][9].

However, little attention has been devoted to a computational modelling perspective on social support networks, on how the dynamics of support seeking and providing work at a societal level. In many ways, the availability of social support is still too frequently viewed as a static facet of individual or environment. However, the support seeking and provision process is highly dynamic and it involves substantial changes as demanding conditions occur [2]. From this dynamic process a collective pattern may emerge that costs almost no effort, and is beneficial for all members. While it is difficult to observe such conditions in the real world, a multiagent system model offers a more convenient perspective. This paper is organized as follows. Section 2 describes the theoretical concepts of support receipt and provision. From this perspective, a formal model is designed and developed (Section 3). Later, in Section 4, several simulation traces are presented to illustrate how this model satisfies the expected outcomes. In Section 5, a mathematical analysis is performed in order to identify possible equilibria in the model. Finally, Section 6 concludes the paper.

2 Antecedents of Social Support Receipt and Provision

Research on social support provides useful information from controlled experimental paradigms on several important factors influenced the possibilities of seeking and giving help. During the formation of stress, there is a condition where an individual either will increase the support interaction demands on support providers. It is typically involves many options, such as whether or not a support provider performs particular support, based on what actions to take and in what manner [1]. Furthermore, through a perspective of help seeking behavior, it also related to the answer of which support member is suitable to pledge for help and so forth. In general, support provision is driven by altruistic intentions and is influenced by several factors that related to provide a support. Within social support researchers' community, it has commonly been viewed that social support is related to several characteristics, namely; (1) stress risk factors, (2) receipt factors, (3) relationship factors, (4) provision factors, and (5) motivation in support [1][3][5][9]. For the first point, stress risk factor is related to the recipient ability to recognize the need of support and be willing to accept support assistance. It includes both features of stressors and appraisal of stressors. This factor is influenced by individual's perceptions of stressors, vulnerability (risk in mental illness), and expectations support from the others [7]. Research indicates that the degree of stressors is correlated to amount of support levels. For example, situations considered as stressful by both support recipients and providers are much more probable to trigger support responses than non-stressful events [2][9]. Having this requirement in motion, potential support providers will recognize the need of support assistance and be willing to offer support [1].

Another point that can be made to understand the social support process is a recipient factor. Despite evidence that primarily shows the negative event plays an important role in seeking and providing support, yet severely distress individuals as experienced by major depression patients seems to reduce social support process. It is highly related to the individual's personality. Normally, a neurotic personality tends to attract a negative relationship between social support provider and social engagement [6]. Studies of the personality and support have documented that individuals with high self-esteem (assertive) receive more social support compared to the individuals with neurotic personality [1][6]. In relationship factors, characteristics of the relationship (ties) between support recipient and provider are equally to important to activate support selection behaviours. It includes mutual interest (experiential and situational similarity), and satisfaction with a relationship. It is eventually becomes a part of socio-cultural system that has a balance between giving and receiving support. In this connection, it should also be mentioned that there are two additional antecedents related closely to the relationship factors. These are acceptance of social norms and reciprocity norms [1]. Social norms are highly

coupled with the view of individual responsibility, intimate relationship and obligation. An example of this is, it is a common fact that many individuals will feel responsible (personal responsibility) for anyone who is dependent upon them. Because of this, it will increase the likelihood of support offering in a certain relationship (either strong tie or weak tie relationship). Strong tie is a relationship typically between individuals in a close personal network. While, a weak tie is typically occurs among individuals who communicate on relatively frequent basis, but do not consider them as close acquaintances. In reciprocity norms, previous interaction and past supportive exchanges will reflect future willingness of both support recipients and providers [2]. Previous failure and frustration of past efforts may influence to reduce individual's motivation and willingness to provide support. For this reason, if individuals always refuse to receive support, it is more likely to receive less support in future [3].

The fourth factor is related to the support provision attributes. Social support members who are faced with condition to give support will be motivated by several factors. Many research works have maintained that there is a link that support-providers with experience empathy and altruistic attitude will regulate altruistic motivation to help the others. In spite of this condition related to the subject of helping people in a weak tie network, it is also useful to understand support's patterns in strong tie network as well. In addition, focus on the other individuals may escalate the potential of providing help through the increasing feeling of empathy, which later develop efficacy. The last factor is the motivation in support. This idea concerns the influence of selecting a support provider from a relationship perspective according to an individual's support need. For example, several studies have shown many individuals with long-term motivation (*future goal orientation*) having difficulty to attain appropriate support from close friends or acquaintances since they feel this group of people has limited skills or knowledge towards the individual's problems [2][3][7]. However, if the individual's intention to seek for emotional support (*emotional goal orientation*) is higher, then they tend to choose a weak tie support over strong tie [7]. Those antecedents also related to explain several individual and interpersonal characteristics that influence an individual's decisions to seek support from particular social network members.

3 A Multi-Agent Model for Social Support Networks

To support the implementation of multiagent system interaction, the dynamic model for both receipt and provision is proposed and designed. This model uses social and behavioural attributes as indicated in a previous section.

3.1 Formalizing the Multi-agent Model

In the agent model used as a basis for the multi-agent system, five main components are interacting to each other to simulate support-seeking and giving behaviours of an agent. These agent components are grouped as; individual receipt and provision attributes, support preference generation, relationship erosion process, stress component, and support feedbacks. Fig.1 illustrates the interaction for these components.

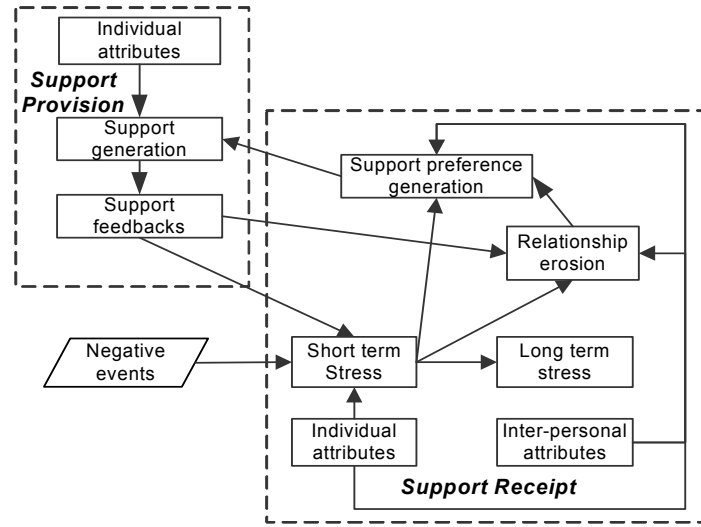


Fig 1. Overall Structure of the Underlying Multi-Agent Model.

As illustrated in Fig.1, negative events acts as an external factor stimulus triggers the stress component. Such a stress condition is amplified by individual receipt attributes such as risk of stress (or risk of mental illness) and neurotic personality, which later accumulates in certain periods to develop a long-term stress condition. The short-term stress also plays an important to evoke support preference pertinent to the receipt attributes.

Similarly, this triggered information will be channelled to the social erosion component, which acts to diminish individual's ability in seeking help. After the social support-tie preference is selected, then the support generation is regulated. Support provision attributes will determine the level of support feedbacks towards the support recipient. To simplify this interaction process, this model assumes all support feedbacks received provide a positive effect towards the agent's well-being (stress-buffering mechanism). Finally, the channelled social support feedback also will be regulated to reduce the relationship erosion effect within individual. The arrows represent the piece of information that the output

of one course of action serves as input for another process. The detailed components of this model are depicted in Fig. 2.

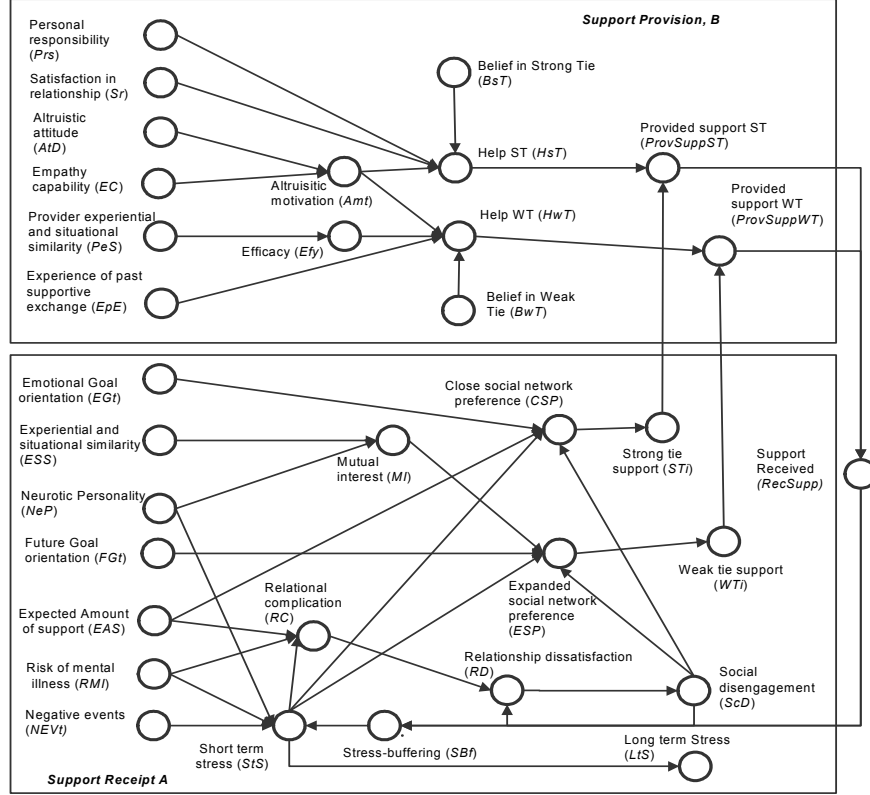


Fig 2. Overall Structure of the Underlying Multi-Agent Model.

As can be seen from Fig. 2, several exogenous variables represent individual support receipt and providing attributes. The results from these variables interaction form several relationships, namely instantaneous and temporal relations. To represent these relationships in agent terms, each variable will be coupled with an agent's name (A or B) and a time variable t . When using the agent variable A , this refers to the agent's support receipt, and B to the agent's support provision. This convention will be used throughout the development of the model in this paper.

3.2 The Agent Component for Support Receipt

This component aims to explain the internal process of support preference during the presence of stress. In general, it combines three main concepts, namely support goal orientation (emotional goal orientation (EGt), future goal orientation (FGt), expected amount of support (EAS)), personality (neurotic (NeP), risk of mental illness/vulnerability (RMI), experiential and situational similarity (ESS)), and external factor (negative events ($NEVt$)). Interactions among these exogenous variables are derived from these formulae.

Mutual Interest: Mutual interest (MI) is calculated using the combination of experiential situational similarity (ESS) and complement relation of neurotic personality (NeP) as opposed to positive personality). That is to say, having a positive personality and a common experience will encourage a better mutual interest engagement.

$$MI_A(t) = ESS_A(t) \cdot (1 - NeP_A(t)) \quad (1)$$

Stress Buffering: Stress buffering (SBf) is related to the presence of support and the level of social disengagement (ScD). Note that, $\eta_{bf,a}$ regulates the level for both support ties contribution. Note that a high social disengagement level ($ScD \rightarrow 1$) will cause stress buffering becomes less effective to curb the formation of stress.

$$SBf_A(t) = RecSupp_A(t) \cdot (1 - ScD_A(t)) \quad (2)$$

Short-Term Stress: Short-term stress (StS) refers to the combination of negative events, risk in mental illness (vulnerability), and neurotic personality. The contribution of these variables are distributed using regulator parameter $\psi_{st,a}$. If $\psi_{st,a} \rightarrow 1$, then the short-term stress will carry only all information from the external environment, rather than individual attributes. In addition, stress-buffering factor eliminates the effect of short-term stress.

$$StS_A(t) = [\psi_{st,A} \cdot NEVt_A(t) + (1 - \psi_{st,A}) \cdot RMI_A(t) \cdot NeP_A(t)] \cdot (1 - SBf_A(t)) \quad (3)$$

Relational Complication and Relational Dissatisfaction: Relation complication (RC) is measured using the contribution rate (determined by γ_r) of the expected support (EAS) and short-term stress (StS). Related to this, relational dissatisfaction (RD) is determined by η_{rd} times relational complication when no support is given.

$$RC_A(t) = \gamma_{r,A} \cdot EAS_A(t) \cdot StS_A(t) \quad (4)$$

$$RD_A(t) = \eta_{rd,A} \cdot RC_A(t) \cdot (1 - RecSupp_A(t)) \quad (5)$$

Close and Expanded Support Preferences: Close support preference (CSP) depends to the level of emotional goal orientation (EGt), short-term stress (StS), and social disengagement (ScD). In the case of extended support preference (ESP), it is calculated using the level of future goal orientation (FGt), short-term stress, mutual interest, and social disengagement. In both preferences, the presence of social disengagement decreases the social network preference level. Similar circumstance also occur when $StS \rightarrow 0$. Parameters β_{esp} and η_{esp} provide a proportional contribution factor in respective social network preference attributes.

$$CSP_A(t) = [\beta_{esp,A} \cdot EGt_A(t) + (1 - \beta_{esp,A}) \cdot (1 - ScD_A(t))] \cdot StS_A(t) \quad (6)$$

$$ESP_A(t) = [\eta_{esp,A} \cdot FGt_A(t) + (1 - \eta_{esp,A}) \cdot MI_A(t) \cdot (1 - ScD_A(t))] \cdot StS_A(t) \quad (7)$$

Dynamics of Support, Social Disengagement, and Long Term Stress:

In addition, there are four temporal relationships are involved, namely strong-tie preference (Sti), weak-tie preference (WTi), social disengagement (ScD), and long-term stress (LtS). The rate of change for all temporal relationships are determined by flexibility parameters, φ_{sti} , ϕ_{wti} , η_{scd} , and β_{ltS} respectively.

$$ScD_A(t+\Delta t) = ScD_A(t) + \eta_{scd,A} \cdot (1 - ScD_A(t)) \cdot (RD_A(t) - \psi_{scd,A} \cdot ScD_A(t)) \cdot ScD_A(t) \cdot \Delta t \quad (8)$$

$$LtS_A(t+\Delta t) = LtS_A(t) + (\beta_{ltS,A} \cdot (1 - LtS_A(t)) \cdot (StS_A(t) - \xi_{ltS,A} \cdot LtS_A(t))) \cdot LtS_A(t) \cdot \Delta t \quad (9)$$

$$Sti_A(t+\Delta t) = Sti_A(t) + (\varphi_{sti,A} \cdot (1 - Sti_A(t)) \cdot (CSP_A(t) - \phi_{sti,A} \cdot Sti_A(t))) \cdot Sti_A(t) \cdot \Delta t \quad (10)$$

$$WTi_A(t+\Delta t) = WTi_A(t) + (\phi_{wti,A} \cdot (1 - WTi_A(t)) \cdot (ESP_A(t) - \eta_{wti,A} \cdot WTi_A(t))) \cdot WTi_A(t) \cdot \Delta t \quad (11)$$

The current value for all of these temporal relations is related to the previous respective attribute. For example, in the case of Sti , when CSP is higher than the previous strong-tie preference multiplied with the contribution factor, ψ_{sti} , then the strong-tie preference increases. Otherwise, it decreases depending on its previous level and contribution factor. It should be noted that the change process is measured in a time interval between t and $t+\Delta t$.

3.3 The Agent Component for Support Provision

Another important component to regulate support within social networks is the ability to provide help. In many ways, support provision attributes are often correlated to the amount of support provided to the support recipients.

Antecedents of support provision are associated to personal responsibility (PrS), satisfaction in relationship (Sr), altruistic attitudes (AtD), empathy level /capability (EC), provision experiential and situational similarity (PeS), and experience of past supportive exchange (EpE). Combining these factors respectively, instantaneous relationships of altruistic motivation, and efficacy can be derived.

Altruistic Motivation and Efficacy: Altruistic motivation (Amt) is determined by through the combination of individual's attributes in altruistic attitude and empathy capability. In efficacy (Efy), the current contribution to generate efficacy is based on proportional value γ_{efB} towards provision experiential and situational similarity.

$$Amt_B(t) = AtD_B(t).EL_B(t) \quad (12)$$

$$Efy_B(t) = \gamma_{efB} . PeS_B(t) \quad (13)$$

Help Provision of Strong and Weak Tie Support: In help provision, it generates support provision capability to provide help, pertinent to the level of respective attributes and relations. For example, the help provision in strong tie support (HS_T) is calculated from the level of altruistic motivation, personal responsibility, and satisfaction in relationship. The contribution from these factors is regulated using regulation parameter μ_{wst} . In addition, belief on strong tie (BsT) controls the help provision towards support recipients. The same concept also applies for help provision in weak tie support (HW_T).

$$HS_T_B(t) = [(\mu_{wst,B}.Amt_B(t) + (1-\mu_{wst,B}).Sr_B(t).PrS_B(t))].BsT(t) \quad (14)$$

$$HW_T_B(t) = [(\mu_{wst,B}.Efy_B(t) + (1-\mu_{wst,B}).Amt_B(t).PrS_B(t))].BsT(t) \quad (15)$$

For both cases, these beliefs regulate the level of generated help for later usage in the provided support. Having no belief concerning support causes no support will be provided to the support recipients.

3.4 Social Support Distribution and Aggregation

Within the provided support, there are two main components are implemented to regulate support distribution among agents. The first component is a mechanism to differentiate the strong tie ($ProvSuppST_{B,A}$) or weak tie ($ProvSuppWT_{B,A}$) support provision offered by a support provision agent to multiple support receipt agents. By using this technique, the overall support is distributed over the support receipt agents with the proportional to the level of support that respective agents requested for. Later, the received support

($RecSupp_A$) is aggregated by multiple support provision agents to each support receipt agent accordingly.

$$ProvSuppST_{B,A} = (STi_A / \sum_A STi_A) \cdot HsT_B \cdot (1 - \prod_A (1 - STi_A)) \quad (16)$$

$$ProvSuppWT_{B,A} = (WTi_A / \sum_A WTi_A) \cdot HwT_B \cdot (1 - \prod_A (1 - WTi_A)) \quad (17)$$

$$RecSupp_A = 1 - [(\prod_B (1 - ProvSuppST_{B,A})) \cdot (1 - ProvSuppWT_{B,A})] \quad (18)$$

4 Results

This section addresses analysis of the multiagent model using several simulation experiments. By variation of the personality attributes for support receipt and provision agents, some typical patterns can be found. Due to the excessive number of possible combinations, this paper shows example runs for four agents under two conditions, namely prolonged and fluctuated stressor events with a different personality profile. Table 1 outlines the values of these profile attributes.

Table 1. Individual Profiles for Each Agent.

Support Receipt Agents	Personality Attributes (<i>EGt, ESS, NeP, FGt, EAS, RMt</i>)
A1	0.8,0.7,0.8,0.7,0.8,0.8
A2	0.8,0.6,0.2,0.9,0.1,0.3
Support Provision Agents	Personality Attributes (<i>PrS, Sr, EL, AtD, PeS, EpE</i>)
B1	0.7,0.8,0.8,0.9,0.7,0.9
B2	0.7,0.7,0.3,0.4,0.6,0.7

The duration of the scenario is up to 1000 time points with these simulation settings;

$$\begin{aligned} \Delta t &= 0.3, \\ \phi_{sti} &= \phi_{wti} = \eta_{scd} = \beta_{lis} = 0.2, \\ \psi_{sts} &= \mu_{wst} = \beta_{exp} = \eta_{esp} = \mu_{wmt} = 0.5, \\ \gamma_{rcA} &= \eta_{rd} = \gamma_{efy} = 0.8 \end{aligned}$$

For all cases, if the long term stress is equal or greater than 0.5, it describes the support receipt agent is experiencing stress condition. These experimental results will be discussed in detail below.

Case # 1: Support Provision and Long Term Stress during Prolonged Stressor Events.

For this simulation, all support receipt agents have been exposed to an extreme case of stressor events over period of time. It represents individuals that having a

difficulty throughout their lifetime. The result of this simulation is shown in Figure 3.

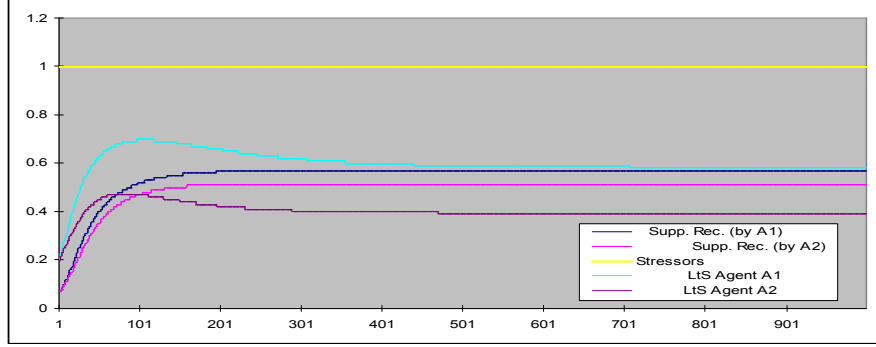


Fig. 3. The Level of Long Term Stress (*LtS*) and Support Received (*Supp. Rec.*) by Agent *A1* and *A2* during Prolonged Stressor.

As can be seen from Figure 3, both agents received supports that allow them to reduce their long-term stress throughout time. The amounts of support received by both agents are varied according to their personality attributes. In this case, agent *A1* received slightly less support compared to its correspondence long-term stress level. This finding is consistent with [6] who found that an individual with a high neurotic personality received less support from either strong or weak social network tie even during stressful event. Thus, agent *A2* recovers faster compared to agent *A1*.

Case # 2: Support Provision and Long Term Stress during Progression of Stressor Events.

In this experiment, both agents are exposed to the progression of stressor event. During this condition, support receipt agent will increase the amount of support needed, and support provision agent will provide certain amount of support with the respect personality attributes. Figure 4 illustrates the progression of stressor, support received, and long term stress for both support receipt agents.

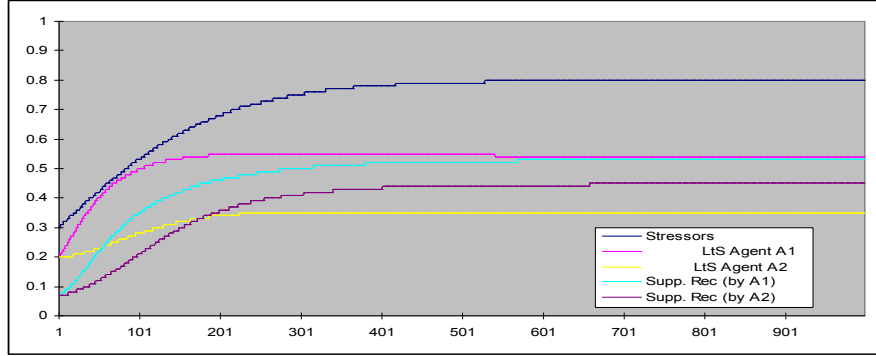


Fig. 4. The Level of Long Term Stress (LtS) and Support Received ($Supp. Rec.$) by Agent $A1$ and $A2$ during Progression Stressor.

Figure 4 indicates that agent $A2$ receives better support compared to $A1$ where, the amount support is slightly higher compared to its long-term stress. Throughout time, it decreases the long-term stress, and providing better coping to curb the progression of it. Compared to agent $A1$, agent $A2$ is unlikely to develop prolonged stress condition.

Case # 3: Support Provision and Long Term Stress During Exposure To Fluctuating Stressor Events.

In the following simulation, two kinds of stressors were introduced to agents $A1$ and $A2$. The first event contains a very high constant stressor, and is followed by the second event with a very low constant stressor.

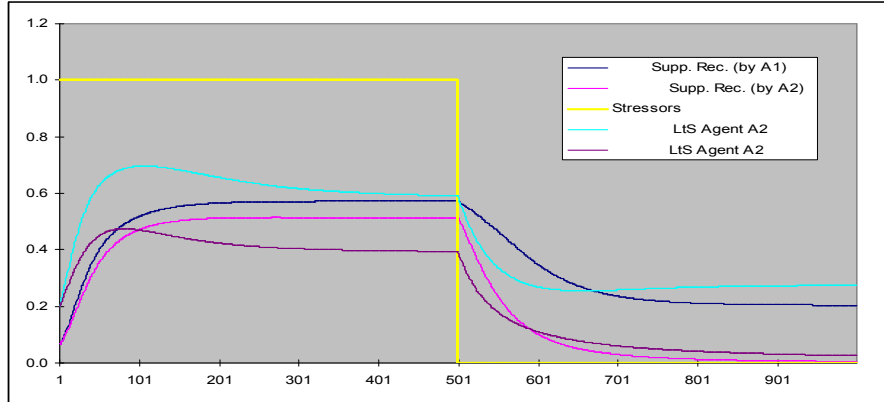


Fig. 5. The Level of Long Term Stress (LtS) and Support Received ($Supp. Rec.$) by Agent $A1$ and $A2$ during Fluctuated Stressor.

As shown in Figure 5, it illustrates the decrease of support level received by both agents. When there is no stressor is experienced by support receipt agents,

the lower of support seeking behavior is reduced. It also worth noting that agent $A1$ shows slightly declining pattern for the long-term stress, compared to agent $A2$ (with considerably decline towards “no stress” condition). This condition explains that individual with risk in mental illness and neurotic personal is vulnerable towards changes in environment [6]. Having these conditions in motion, more effort in support provision is needed to allow better recovery process to take place [3].

5 Mathematical Analysis

One of the aspects that can be addressed by a mathematical analysis is which types of stable situations are possible. To this end equations for equilibria can be determined from the model equations. This can be done to assume constant values for all variables (also the ones that are used as inputs). Then in all of the equations the reference to time t can be left out, and in addition the differential equations can be simplified by canceling, for example, $ScD_A(t+\Delta t)$ against $ScD_A(t)$. This leads to the following equations.

Agent Component for Support Receipt (by A from some B's)

$$MI_A = ESS_A \cdot (1 - NeP_A) \quad (19)$$

$$SBf_A = RecSupp_A \cdot (1 - ScD_A) \quad (20)$$

$$StS_A = [\psi_{st,A} \cdot NEV_{tA} + (1 - \psi_{st,A}) \cdot RMI_A \cdot NeP_A] \cdot (1 - SBf_A) \quad (21)$$

$$RC_A = \gamma_{r,A} \cdot EAS_A \cdot StS_A \quad (22)$$

$$RD_A = \eta_{rd,A} \cdot RC_A \cdot (1 - RecSupp_A) \quad (23)$$

$$CSP_A = [\beta_{esp,A} \cdot EGT_A + (1 - \beta_{esp,A}) \cdot (1 - ScD_A)] \cdot StS_A \quad (24)$$

$$ESP_A = [\eta_{esp,A} \cdot FGT_A + (1 - \eta_{esp,A}) \cdot MI_A \cdot (1 - ScD_A)] \cdot StS_A \quad (25)$$

$$\eta_{sd,A} \cdot (1 - ScD_A) \cdot (RD_A - \psi_{sd,A} \cdot ScD_A) \cdot ScD_A = 0 \quad (26)$$

$$\beta_{ls,A} \cdot (1 - LsA) \cdot (StS_A - \xi_{ls,A} \cdot LsA) \cdot LsA = 0 \quad (27)$$

$$\phi_{sti,A} \cdot (1 - STi_A) \cdot (CSP_A - \phi_{sti,A} \cdot STi_A) \cdot STi_A = 0 \quad (28)$$

$$\phi_{wti,A} \cdot (1 - WTi_A) \cdot (ESP_A - \eta_{wti,A} \cdot WTi_A) \cdot WTi_A = 0 \quad (29)$$

Agent Component for Support Provision (from B to some A's)

$$Amt_B = AtD_B \cdot EL_B \quad (30)$$

$$Efy_B = \gamma_{ef,B} \cdot PeS_B \quad (31)$$

$$HsT_B = [(\mu_{wst,B} \cdot Amt_B + (1 - \mu_{wst,B}) \cdot Sr_B \cdot PrS_B)] \cdot BsT \quad (32)$$

$$HwT_B = [(\mu_{wmt,B} \cdot Efy_B + (1 - \mu_{wmt,B}) \cdot AMT_B \cdot PrS_B)] \cdot BwT \quad (33)$$

Differentiation of Provided Support from B to A

$$ProvSuppST_{B,A} = (STi_A / \sum_A STi_A) \cdot HsT_B \cdot (1 - \prod_A (1 - STi_A)) \quad (34)$$

$$ProvSuppWT_{B,A} = (WTi_A / \sum_A WTi_A) \cdot HwT_B \cdot (1 - \prod_A (1 - WTi_A)) \quad (35)$$

Aggregation of Received Support by A

$$RecSupp_A = 1 - [\prod_B (1 - ProvSupp_{ST_{B,A}}) \cdot (1 - ProvSupp_{WT_{B,A}})] \quad (36)$$

Assuming the parameters $\eta_{sd,A}$, $\beta_{ls,A}$, η_{sd} , β_{ls} nonzero, from the equations (26) to (29), for any agent A the following cases can be distinguished:

$$\begin{array}{llll} ScD_A = 1 & \text{or} & RD_A = \psi_{sd,A} \cdot ScD_A & \text{or} & ScD_A = 0 \\ LtS_A = 1 & \text{or} & StS_A = \xi_{ls,A} \cdot LtS_A & \text{or} & LtS_A = 0 \\ STi_A = 1 & \text{or} & CSP_A = \phi_{sti,A} \cdot STi_A & \text{or} & STi_A = 0 \\ WTi_A = 1 & \text{or} & ESP_A = \eta_{wti,A} \cdot WTi_A & \text{or} & WTi_A = 0 \end{array}$$

For one agent, this amounts to $3^4 = 81$ possible equilibria. Also given the other equations (19) to (25) and (30) to (36) with a large number of input variables, and the number of agents involved, this makes it hard to come up with a complete classification of equilibria. However, for some typical cases the analysis can be pursued further.

Case $ScD_A = 1$

In this case from the equations (20), (24) and (25) it follows:

$$SBf_A = 0, CSP_A = \beta_{sp,A} \cdot EG_{tA}, StS_A, ESP_A = \eta_{sp,A} \cdot FG_{tA}, StS_A$$

This can be used to determine values of other variables by (21), (22), (23), for example.

Case $StS_A = LtS_A = 0$

In this case, from the equations (22), (24) and (25) it follows:

$$RC_A = 0, CSP_A = 0, ESP_A = 0$$

from which, for example, by (23) it follows that $RD_A = 0$.

6 Conclusion

In this paper, a computational model is presented that describes the mechanism of support receipt and provision within a social network. The agent model used is composed of two main components: agent receipt and provision. The first component explains how personality attributes affect support-seeking behavior, ties selection, and stress buffering, and the second one explains how personality attributes affect providing support behaviour. The model has been implemented in a multiagent environment, dedicated to perform simulations using scenarios based on different stressful events over time and personality attributes. Simulation results show interesting patterns that illustrate the relation of support seeking behaviours and level of support received, with long-term stress. A mathematical analysis indicates which types of equilibria are indeed a

consequence of the model. The model can be used as the basis for a personal software agent that facilitates a person in regulating help within a social network member. In addition, using this model, a personal agent will be able to determine social tie selection, and providing information regarding to the level of support needed with correspondence to personality attributes, for both individuals who are seeking and providing support. Thus, this model could possibly be used as a building block for interventions for individual who are facing stress or as a warning system for social support members.

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Chapter 10

Modelling Caregiving Interactions during Stress

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“We don't need sugar, flour or rice or anything else. We just want to see our dear ones.”

(Hafiz of Persia)

Modelling Caregiving Interactions during Stress

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Abstract: Few studies describing caregiver stress and coping have focused on the effects of informal caregiving for depressed care recipients. The major purpose of this paper was to investigate the dynamics of the informal care support and receipt interactions among caregivers and care recipients using a computational modelling approach. Important concepts in coping skills, strong ties support networks and stress buffering studies were used as a basis for the model design and verification. Simulation experiments for several cases pointed out that the model is able to reproduce interaction among strong tie network members during stress. In addition, the possible equilibria of the model have been determined, and the model has been automatically verified against expected overall properties.

Keywords: caregiving process, simulation, depression and stress.

1 Introduction

Caring for a family member, spouse or friend (informal caregiving) who is diagnosed with a severe illness (e.g., a unipolar disorder) can be a stressful experience. While most caregivers adapt well to the situation of caring for a person with a unipolar depression, some do not. A number of studies investigate the negative consequences for the informal caregiver, such as the development of depression, burden, burnout, or (chronic) stress, when caring for elderly patients or patients with illnesses like dementia, or Parkinson's [5], [6], [7], [9], [10]. The current paper addresses the development of stress in informal caregivers of patients with unipolar depression and the effect of this stress on the interactions between the caregiver and care recipient. To understand the caregiver's adaptations to the cognitive disabilities of his/her close acquaintance, the complex nature of stress processes must be accounted for and the constructs and factors that play a function in the caregiving must be considered. For each individual a number of cognitive and physiological mechanisms regulate the impact of stress on health and well-being. Individuals typically occupy multiple roles in life; becoming a caregiver of a person with depression introduces an additional role, and therefore will require some rearrangement of priorities, and redirection of energy [10]. Not only is this likely to produce strain at a personal level, but it is also likely to spur reactions (potentially negative) from diverse people who are interconnected to a person through his or her roles outside the realm of caregiving.

Although much work has been dedicated to understand the caregiving mechanism, little attention has been paid to a computational modelling angle on how caregivers work together to support their close acquaintances under stress. The caregiving process is highly dynamic in nature, and it requires demanding resources to monitor such a process in the real world [6]. The aim of this paper is to present a computational model that can be used to simulate the dynamics in the caregiver and care recipient under influence of external events. The current work is an addition to our previous model of social support selection, where in the current model, individuals with a depressive state are receiving help from close acquaintances [1].

The paper is organized as follows; Section 2 describes several theoretical concepts of social support networks and their relation to stress. From this point of view, a formal model is designed (Section 3). Later in Section 4, a number of simulation traces are presented to illustrate how the proposed model satisfies the expected outcomes. In Section 5, a mathematical analysis is performed in order to identify possible equilibria in the model, followed by verification of the model against formally specified expected overall patterns, using an automated verification tool (Section 6). Finally, Section 7 concludes the paper.

2 Underlying Principles in Informal Caregiving Interactions

Researchers from several domains have become increasingly interested in social support, caregiving, and mental health. For instance, researchers in nursing and healthcare domain have contributed several theories to explain those relationships by presenting foundations on coping behaviours, mediating attributes, caregiving adaptation, and stress. One of the theories that has been used to explain these interactions is the Theory of Caregiver Stress and Coping which combines important principles in Lazarus Stress-Coping Theory, Interpersonal Framework of Stress-Coping, and Stress Process Theory of Pearlin [3] [4] [11].

Within the model introduced, three aspects play important roles to regulate support and maintain the caregiver's personal health: 1) externally generated stressors (negative events), 2) mediating conditions, and 3) caregiver outcomes [4] [6][10]. For the first aspect, stressors are related to specific internal or external demands (*primary stressors*) that the caregiver has to manage. For example, several studies show that sufficient caregiver *personal resources* (e.g. financial incomes, social) reduces the perception of caregiving burden, while a loss of emotional resources (*long term emotional exhaustion*) amplifies the perceived burden [9]. The second aspect represents how the caregiver reacts (coping strategies) when facing the adversity in caregiving. In the proposed model, caregivers who face a primary stressful situation generally use a combination of *problem-focused coping* and *emotion-focused coping*. Problem-focused coping is associated with positive interpersonal efforts to get the problem solved [3].

In contrast to this, emotion-focused coping strategies (thinking rather than acting to change the person-environment relationship) entail efforts to regulate the emotional consequences (e.g. avoidance) of stressful or potentially stressful events [4]. This choice of coping is related to the *caregiver's personality*, for example, a caregiver with a positive personality (e.g., low in neuroticism) tends to choose problem-focused approach [5]. Another important concept that can be derived from these coping strategies is *the relationship focused coping* (positive or negative). The combination of high caregiver's *empathy* (perceiving the inner feeling of care recipient) and problem-focused coping will lead to *positive relationship coping*, and vice versa [4] [7] [8]. The third aspect is related to the caregiver's outcome. Mainly, this component ranges on a continuum from *bonadaptation* (meeting the needs to support the care recipient) to *maladaptation* (continued negative situation and need for referral and assistance) [4] [11]. In addition to this, bonadaptation is related to the high personal accomplishment (*expected personal gain*) and provided support (*social support*), while maladaptation is linked to the *emotional exhaustion* [9]. A high expected personal gain reduces the *short term* and *long term stress level* in caregivers, which will improve interaction during the caregiving process [7]. When the care recipients receive support, it will reduce their stress by the

resource serves as an insulating factor, or *stress buffer*, so that people who have more social support resources are less affected by negative events [5] [6].

3 Modeling Approach

Based on the analysis of the dynamics in coping behaviours, mediating attributes, caregiving adaptation, and stress, as given in the previous section, it is possible to specify computational properties for the multi-agent model. The results from the interaction between these variables form several relationships, both in instantaneous and in temporal form. To represent these relationships in agent terms, each variable will be coupled with an agent's name (A or B) and a time variable t . When using the agent variable A , this refers to the caregiver agent and B to the care recipient agent. This convention will be used throughout the development of the model in this paper. The details of this model are shown in Fig. 1.

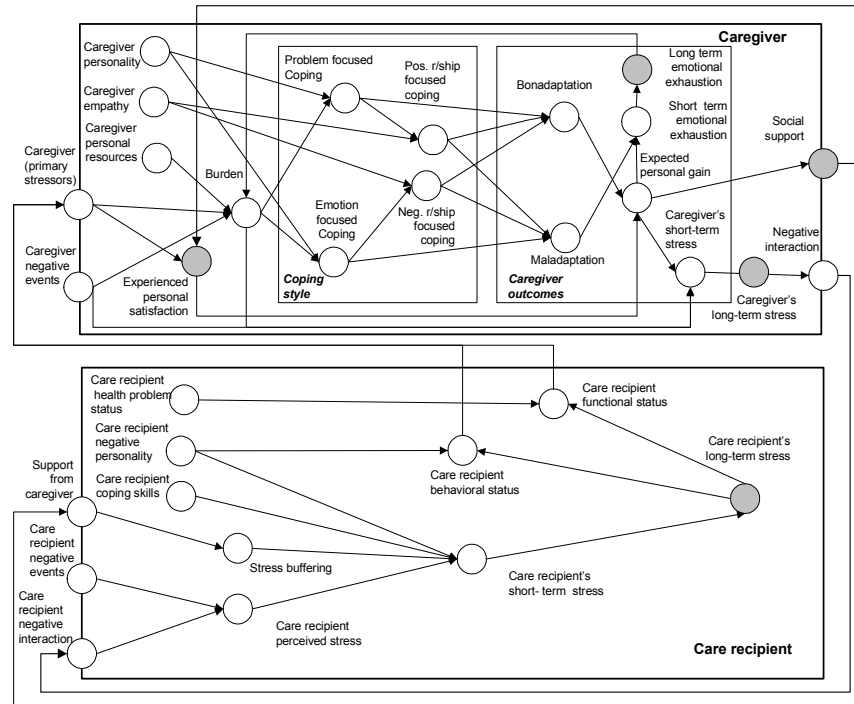


Fig. 1. Global Relationship of Variables Involved in the Caregiving Interactions during Stress.

3.1. The Caregiver Model

This component of the overall model aims to formalise important concepts within the caregiver. The instantaneous relationships are expressed as follows. The problem-focused coping PfC is calculated using the combination of the caregiver personality GpP and burden Bd . Note that a high burden level close to 1 will have the effect that the choice of using problem focused coping becomes smaller.

$$PfC_A(t) = GpP_A(t).(1-Bd_A(t)) \quad (1)$$

$$EfC_A(t) = (1-GpP_A(t)).Bd_A(t) \quad (2)$$

However in emotional-focused coping EfC , those factors provide a contrasting effect. Positive relationship focused coping ($RfC+$) depends on the relation between problem focused coping and caregiver's empathy. A high empathy will increase this function, while reducing its counterpart (negative relationship focused coping ($RfC-$)).

$$RfC_A^+ = PfC_A(t).GE_A(t) \quad (3)$$

$$RfC_A^- = EfC_A(t).(1-GE_A(t)) \quad (4)$$

Burden (Bd) is determined by regulating proportional contribution β between caregiver primary stressors (GpS), long term emotional exhaustion (ExH), and caregiver resources (GpR). Expected personal gain (PgN) is measured using the proportional contribution (determined by σ) of the bonadaption (Bn) and experienced personal satisfaction EpN . Short term emotional exhaustion EsH is measured by combining maladaption Md and negative relationship of expected personal gain.

$$Bd_A(t) = [\beta.GpS_A(t) + (1-\beta).ExH_A(t)].(1-GpR_A(t)) \quad (5)$$

$$PgN_A(t) = \sigma.Bn_A(t) + (1-\sigma).EpN_A(t) \quad (6)$$

$$EsH_A(t) = Md_A(t).(1-PgN_A(t)) \quad (7)$$

Caregiver short term stress GsS is related to the presence of caregiver negative events GnE and burden Bd . Note that a high expected personal gain will reduce the short term stress level. The maladaptation Md is calculated using the combination of negative ($RfC-$), positive, relationship, and emotional-focused coping. In the case of bonadaptation, it is determined by measuring the level of positive, negative, relationship, and problem-focused coping. Parameters ϕ , γ , and ρ provide a proportional contribution factor in respective relationships. In addition to the instantaneous relations, there are four temporal relationships involved, namely experienced personal satisfaction EpN , long term emotional exhaustion ExH , caregiver long term stress GsS , and social support SsP . The rate

of change for all temporal relationships are determined by flexibility rates, γ , ϑ , ϕ , and ψ , respectively

$$Gs_A(t) = [\phi.GnE_A(t) + (1-\phi).Bd_A(t)].(1-PgN_A(t)) \quad (8)$$

$$Md_A(t) = [\gamma.RfC_A(t) + (1-\gamma).EfC_A(t)].(1-RfC_A^+(t)) \quad (9)$$

$$Bn_A(t) = [\rho.RfC_A^+(t) + (1-\rho).PfC_A(t)].(1-RfC_A(t)) \quad (10)$$

The current value for all of these temporal relations is related to the previous respective attribute. It should be noted that the change process is measured in a time interval between t and $t+\Delta t$. The operator Pos for the positive part is defined by $Pos(x) = (x + |x|)/2$, or alternatively; $Pos(x) = x$ if $x \geq 0$ and 0 else.

$$ExH_A(t+\Delta t) = ExH_A(t) + \gamma.[Pos(ExH_A(t) - ExH_A(t)).(1-ExH_A(t)) - Pos(-(ExH_A(t) - ExH_A(t)).ExH_A(t))].\Delta t \quad (11)$$

$$EpN_A(t+\Delta t) = EpN_A(t) + \vartheta.[Pos((S\phi_A(t) - GpS_A(t)) - EpN_A(t)).(1-EpN_A(t)) - Pos(-(S\phi_A(t) - GpS_A(t)) - EpN_A(t)).EpN_A(t)].\Delta t \quad (12)$$

$$Gls_A(t+\Delta t) = GlS_A(t) + \phi.(Gs_A(t) - GlS_A(t)).(1 - GlS_A(t)).GlS_A(t).\Delta t \quad (13)$$

$$ScP_A(t+\Delta t) = ScP_A(t) + \psi.[Pos(PgN_A(t) - ScP_A(t)).(1-ScP_A(t)) - Pos(-(PgN_A(t) - ScP_A(t)).ScP_A(t))].\Delta t \quad (14)$$

3.2. The Care Recipient Model

The care recipient model is another interacting components in the overall model. It has five instantaneous relations (care recipient perceived stress RpS , stress buffer SbF , care recipient short term stress RcS , care recipient functional RfS , and behavioural status RbS) and one temporal relation (care recipient long term stress RlS).

$$RpS_B(t) = \tau.RnI_B(t) + (1-\tau).RnE_B(t) \quad (15)$$

$$SbF_B(t) = \omega.RcG_B(t) \quad (16)$$

$$RcS_B(t) = [\lambda.RpB(t) + (1-\lambda).(1-RcS_B(t))].RpS_B(t).(1-SbF_B(t)) \quad (17)$$

$$RfS_B(t) = RbS_B(t).RlS_B(t) \quad (18)$$

$$RbS_B(t) = RpB(t).RlS_B(t) \quad (19)$$

$$RlS_B(t+\Delta t) = RlS_B(t) + \eta.(RcS_B(t) - RlS_B(t)).(1-RlS_B(t)).RlS_B(t).\Delta t \quad (20)$$

Care recipient perceived stress is modelled by instantaneous relations (regulated by a proportional factor τ) between the care recipient negative interactions RnI and events RnE . Stress buffer is determined by ω times received support RSG . Care recipient short term stress depends on the relation between stress buffer SbF , and the proportion contribution λ of care recipient coping skills RcS , perceived stress RpS , and negative personality RpS . For the care recipient functional and behaviour status levels, both of these relations are calculated by multiplying the value of care recipient health problem status RbS and negative personality Rp with care recipient long term stress RS respectively. In addition, the temporal relation of care recipient long term stress is contributed from the accumulation exposure towards care recipient short term stress with the flexibility rate η .

4 Simulation Results

In this section, a number of simulated scenarios with a variety of different conditions of individuals are discussed. Only three conditions are considered: prolonged, fluctuated stressor, and non-stressful events with a different personality profile. For clarity, cg and cr denotes caregiver and care recipient agent profiles respectively. The labels ‘good’ and ‘bad’ in Table 1 can also be read as ‘effective’ and ‘ineffective’ or ‘bonadaptive’ and ‘maladaptive’.

Table 1: Individual Profiles.

Caregiver	GpR	GE	GpP
cg1 (‘good’ caregiver)	0.8	0.7	0.7
cg2 (‘bad’ caregiver)	0.1	0.2	0.2
Care recipient	RhS	Rp	RcS
cr1 (‘good’ coping skills)	0.9	0.9	0.8
cr2 (‘bad’ coping skills)	0.9	0.9	0.1

Corresponding to these settings, the level of severity (or potential onset) is measured, defining that any individual that scored more than 0.5 in their long term stress level (within more than 336 time steps) then the caregiver or support receipt agent will be experiencing stress. There are several parameters that can be varied to simulate different characteristics. However, the current simulations used the following parameters settings: $t_{max}=1000$ (to represent a monitoring activity up to 42 days), $\Delta t=0.3$, (flexibility rate) $\varphi=\eta=\theta=\psi=\gamma=0.3$, (regulatory rate) $\sigma=\beta=\chi=\rho=\sigma=\phi=\tau=\lambda=0.5$, $\omega=\xi=0.8$. These settings were obtained from previous systematic experiments to determine the most suitable parameter values in the model.

Result # 1: Caregiver and receiver experience negative events.

During this simulation, all agents have been exposed to an extreme case of stressor events. This kind of pattern is comparable to the prolonged stressors throughout a life time. For the first simulation trace (Fig. 2(a)), a good caregiver tends to provide a good social support provision towards its care recipient even facing persistent heightened stressors. This pattern is in line with the findings reported in [5]. One of the factors can be used to explain this condition is the increasing level of caregiver's personal gain. It proposes that caregivers do not unequivocally view caregiving as an overwhelmingly negative experience but can appraise the demands of caregiving as rewarding [4] [9]. Previous research works has also suggests that caregiving satisfaction is an important aspect of the caregiving experience and seem to share parallel relationships with other variables (e.g, personality and empathy) [4] [11].

Moreover, a good caregiver normally uses a problem focused coping to solve the perceived problem and later increases positive relationship focused coping. By the same token, research has consistently established a significant relationship between personal gains, problem focused coping, and positive social support. For example, several studies reported that caregivers who were satisfied with caregiving used more problem-focused coping [3]. Having this in motion, it provides a positive view of social support and later will be translated as a support received by the care recipient.

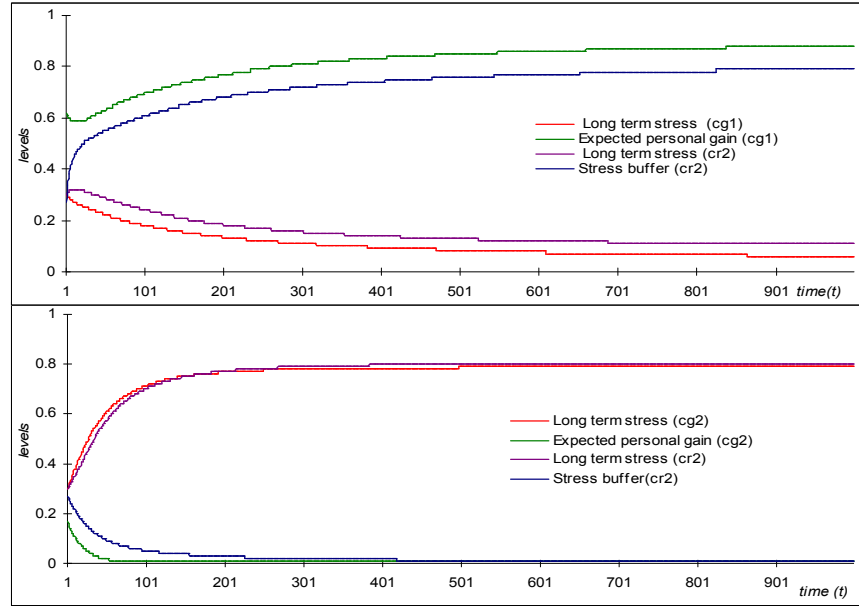


Fig. 2. Simulation traces during prolonged stressors for (a, upper graph) a good caregiver and bad care recipient (b, lower graph) a bad caregiver and bad recipient.

In the second simulation trace (as shown in Fig. 2(b)), both agents (caregiver and care recipient) are facing high long term stress levels in the long run. The precursors of having these conditions are perception of caregiving as a burden and the inability of the caregiver to provide positive coping during stressful events [11]. These factors lead to the decreasing level of caregiver's positive relationship focused coping and experienced personal gain, and later will reduce the ability to provide support. Additionally, in the real world, it can be perceived as feeling overwhelmed and out of control of the situation. This condition occurs almost within the majority of caregivers when they feel burdened by the demands of caregiving [6].

Result # 2: Caregiver and receiver experience different types of negative events. In this simulation, a new kind of stressor was introduced. This stressor comprises two parts: the first part is one with very high constant prolonged stressors, and is followed by the second one, with a very low stressor event. During simulation, the caregiver agents (cg1 and cg2) were exposed towards these stressors, while the care recipient agents will only experience prolonged stressors. As it can be seen from Fig. 3(a), the graph indicates both agents (cg1 and cr2) experience gradual drops in their long term stress.

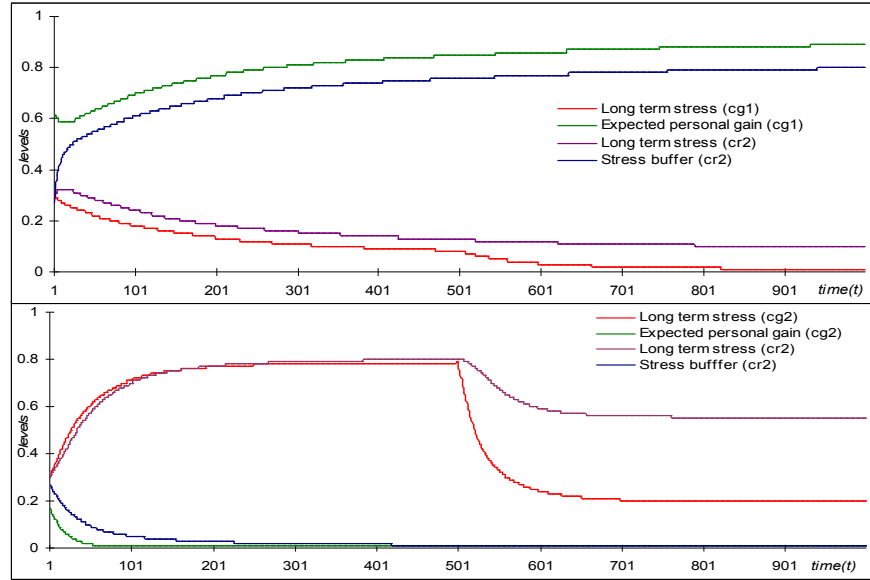


Fig. 3. Simulation traces during different stressors for (a, upper graph) a good caregiver and bad care recipient (b, lower graph) a bad caregiver and bad recipient.

Comparison between Fig. 3(a) and Fig. 3(a), shows that the scenario's almost have a similar pattern, but 3(a) has a substantial decrease in a caregiver's long term stress level after the first half of the simulation. It is consistent with the findings that caregivers with a positive personality, empathic, and high personal resources tend to help more if they experienced less negative event [3], [8]. Meanwhile, Fig. 3(b) provides different scenarios. The simulation results show that caregivers with a negative personality, less empathic, and low personal resources is incapable to provide support during caregiving process. Note that despite the caregivers experience non-stressor events after the first half of the simulation, their care recipient is still experiencing a high long term stress level. Similar findings can be found in [5] [10].

Result # 3: Managing a good care recipient. In this part, simulation was carried out to investigate the effects of the caregiving behaviours of caregiver agents with different profiles to good care recipients, during prolonged negative stressors. Interaction between good caregiver and recipient shows that both agents have low long term stress levels, while the recipients stress buffer and the caregiver's expected personal gain are increasing [5] [7]. On the contrary, interaction between bad caregiver and good care recipient indicates that both agents are experiencing high long term stress levels. However, the care recipient experiences lesser long term stress compared to the caregiver.

5 Mathematical Analysis

In this section it is discussed which equilibria value are possible for the model, i.e., values for the variables of the model for which no change will occur. As a first step the temporal relations for both caregiver and care recipient will be inspected (refer to the equations (11),(12),(13),(14),and (20)). An equilibrium state is characterised by:

$$\begin{aligned} ExHA(t+\Delta t) &= ExHA(t), \\ ScPA(t+\Delta t) &= ScPA(t), \\ GLSA(t+\Delta t) &= GLSA(t), EpNA(t+\Delta t)=EpNA(t), \text{ and} \\ RLSB(t+\Delta t) &= RLSB(t). \end{aligned}$$

Assuming $\gamma, \psi, \Phi, \Theta$ nonzero, and leaving out t , this is equivalent to:

$$\begin{aligned} [(Pos(ExHA-ExHA).(1-ExHA)) - Pos(-(ExHA-ExHA).ExHA)] &= 0 \\ [(Pos(PgNA-ScPA).(1-ScPA)) - Pos(-(PgNA-ScPA).ScPA)] &= 0 \\ (GLSA-GLSA).(1-GLSA).GLSA &= 0 \end{aligned}$$

$$[(Pos((ScPA-GpSA)-EpNA).(1-EpNA))-Pos(-(ScPA-GpSA)-EpNA).EpNA] = 0 \\ (RsSB-RlsB).(1-RlsB).RlsB = 0$$

These equations are equivalent to:

$$(EsHA-ExHA).(1-ExHA) = 0 \text{ and } (EsHA-ExHA).ExHA = 0 \\ (PgNA-ScPA).(1-ScPA) = 0 \text{ and } (PgNA-ScPA).ScPA = 0 \\ (GlsA-GsA).(1-GsA).GlsA = 0 \\ ((ScPA-GpSA)-EpNA).(1-EpNA) = 0 \text{ and } \\ ((ScPA-GpSA)-EpNA).EpNA = 0 \\ RlsB = RsSB \text{ or } RlsB = 0 \text{ or } RlsB = 1$$

These have the following solutions

$$EsHA = ExHA \quad (21)$$

$$PgNA = ScPA \quad (22)$$

$$GlsA = GsA \text{ or } GlSA = 0 \text{ or } GlSA = 1 \quad (23)$$

$$ScPA-GpSA = EpNA \quad (24)$$

$$RlsB = RsSB \text{ or } RlsB = 0 \text{ or } RlsB = 1 \quad (25)$$

This means that for the caregiver short term and long term emotional exhaustion are equal (21). Also for both the caregiver and the care recipient short term and long term stress are the same, when the long term stress is not 0 or 1 (23) and (25). Moreover, for the caregiver social support provision is equal to expected personal gain (22), and on the other hand social support provision is equal to the sum of experienced personal gain and the caregiver's primary stressors (24).

6 Formal Verification of the Model

This section addresses the analysis of the informal caregiving interactions model by specification and verification of properties expressing dynamic patterns that are expected to emerge. The purpose of this type of verification is to check whether the model behaves as it should by running a large number of simulations and automatically verifying such properties against the simulation traces. A number of dynamic properties have been identified, formalized in the language TTIL and automatically checked [2]. The language TTIL is built on atoms $state(\gamma, t) \models p$ denoting that p holds in trace γ (a trajectory of states over time). Dynamic properties are temporal predicate logic statements that can be formulated using such state atoms. Below, a some of the dynamic properties that were identified for the informal caregiving interactions model are introduced, both in semi-formal and in informal notation. Note that the properties are all defined for a particular trace γ or a pair of traces γ_1, γ_2 .

P1 : Stress Level of agent cg

For all time points $t1$ and $t2$ in traces $\gamma1$ and $\gamma2$

if in trace $\gamma1$ at $t1$ the level of negative life events of agent cg is $x1$ and in trace $\gamma2$ at $t1$ the level of negative life events of agent CG is $x2$, and in trace $\gamma1$ at $t1$ the level of personal resources of agent cg is $y1$ and in trace $\gamma2$ at $t1$ the level of personal resources of agent cg is $y1$, and in trace $\gamma1$ at $t1$ the level of long term stress of agent cg is $z1$ and in trace $\gamma2$ at $t1$ the level of caregiver stress of agent cg is $z2$, and $x1 \geq x2$, and $y1 \leq y2$, and $t1 < t2$,

then $z1 \geq z2$.

$P1 \equiv \forall \gamma1, \gamma2: \text{TRACE}, \forall t1, t2: \text{TIME} \forall x1, x2, y1, y2, z1, z2: \text{REAL}$

$\text{state}(\gamma1, t1) \models \text{negative_life_events}(\text{agent}(cg), x1) \ \&$

$\text{state}(\gamma2, t1) \models \text{negative_life_events}(\text{agent}(cg), x2) \ \&$

$\text{state}(\gamma1, t1) \models \text{personal_resources}(\text{agent}(cg), y1) \ \&$

$\text{state}(\gamma2, t1) \models \text{personal_resources}(\text{agent}(cg), y2) \ \&$

$\text{state}(\gamma1, t2) \models \text{long_term_stress}(\text{agent}(cg), z1) \ \&$

$\text{state}(\gamma2, t2) \models \text{long_term_stress}(\text{agent}(cg), z2) \ \&$

$x1 \geq x2 \ \& \ y1 \leq y2 \ \& \ t1 < t2 \Rightarrow z1 \geq z2$

Property P1 can be used to check whether caregivers with more stressful life events and lack of resources will experience a higher level of caregiver (long term) stress. The property succeeded when two traces were compared where in one trace the caregiver had more (or equal) negative life events and less personal resources than the caregiver from the other trace. In this situation the first caregiver experienced more long term stress than the caregiver with more personal resources and less negative life events. Notice that since this property checks whether it is true for all time points in the traces, in some simulation traces the values for negative life events or personal resources change halfway the simulation trace, then the property succeeds for only a part of the trace, which can be expressed by an additional condition stating that $t1$ is at time point 500 (halfway our traces of 1000 time steps).

P2: Stress buffering of agent cr

For all time points $t1$ and $t2$ in trace γ ,

If at $t1$ the level of received social support of agent cr is $m1$, and $m1 \geq 0.5$ (high) and at time point $t2$ the level of the stress buffer of agent cr is $m2$ and $t2 \geq t1 + d$,

then $m2 \geq 0.5$ (high).

$P2 \equiv \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME} \forall m1, m2, d: \text{REAL}$

$\text{state}(\gamma, t1) \models \text{received_social_support}(\text{agent}(cr), m1) \ \&$

$$\text{state}(\gamma, t2) \models \text{stress_buffer}(\text{agent}(\text{cr}), m2) \ \& \\ m1 \geq 0.5 \ \& \ t2 = t1 + d \Rightarrow m2 \geq 0.5$$

Property P2 can be used to check whether social support buffers the care recipient's stress. It is checked whether if the received social support in agent cr is high (a value higher or equal to 0.5), then the stress buffer of agent cr also has a high value after some time (having a value above or equal to 0.5). The property succeeded on the traces, where the received social support was higher or equal to 0.5.

Relating positive recovery of care receiver and social support from caregiver.

Property P3 can be used to check whether positive recovery shown by the care recipient, will make the caregiver provide more social support at a later time point. This property P3 can be logically related to milestone properties P3a and P3b that together imply it: $P3a \ \& \ P3b \Rightarrow P3$. Given this, using the checker it can be found out why a hierarchically higher level property does not succeed. For example, when property P3 does not succeed on a trace, by the above implication it can be concluded that at least one of P3a and P3b cannot be satisfied. By the model checker it can be discovered if it is property P3a and/or P3b that does/do not succeed. Properties P3a and P3b are introduced after property P3 below.

P3 : Positive recovery of agent cr leads to more social support from agent cg

For all time points t1 and t2 in trace γ ,

If at time point t1 the level of primary stressors of agent cg is d1
 and at time point t2 the level of primary stressors of agent cg is d2
 and at time point t1 the level of received support of agent cr is f1
 and at time point t2 the level of received support of agent cr is f2
 and $d2 \geq d1$, and $t1 < t2$,

then $f2 \geq f1$.

$P3 \equiv \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME} \ \forall d1, d2, f1, f2: \text{REAL}$

$\text{state}(\gamma, t1) \models \text{primary_stressors}(\text{agent}(\text{cg}), d1) \ \&$

$\text{state}(\gamma, t2) \models \text{primary_stressors}(\text{agent}(\text{cg}), d2) \ \&$

$\text{state}(\gamma, t1) \models \text{received_social_support}(\text{agent}(\text{cr}), f1) \ \&$

$\text{state}(\gamma, t2) \models \text{received_social_support}(\text{agent}(\text{cr}), f2) \ \&$

$d2 < d1$

$t1 < t2 \Rightarrow f2 \geq f1$

Property P3 succeeded in all generated simulation traces: when the primary stressors of the caregiver decreased, then at a later time point the received social support of the care recipient increased. In some simulation traces the property only succeeded on the first or second half of the trace. In these traces the primary stressors of the caregiver increased in the first part of the trace and then decreased in the second part of the trace. For this, a condition was added to the antecedent of the formal property, namely $t1 = 500$ or $t2 = 500$, so that the property is only checked on the second part or first part of the trace respectively.

P3a: Positive Recovery of agent cr leads to more Personal Gain in Agent cg

For all time points $t1$ and $t2$ in trace γ ,
 If at $t1$ the level of primary stressors of agent cg is $d1$
 and at time point $t2$ the level of primary stressors of agent cg is $d2$
 and at time point $t1$ the level of personal gain of agent cg is $e1$
 and at time point $t2$ the level of personal gain of agent cg is $e2$
 and $d2 \leq d1$,
 and $t1 < t2$

Then $e2 \geq e1$.

$P3a \equiv \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME} \forall d1, d2, e1, e2: \text{REAL}$

$\text{state}(\gamma, t1) \models \text{primary_stressors}(\text{agent}(cg), d1) \ \&$

$\text{state}(\gamma, t2) \models \text{primary_stressors}(\text{agent}(cg), d2) \ \&$

$\text{state}(\gamma, t1) \models \text{expected_personal_gain}(\text{agent}(cg), e1) \ \&$

$\text{state}(\gamma, t2) \models \text{expected_personal_gain}(\text{agent}(cg), e2) \ \&$

$d2 < d1 \ \& \ t1 < t2 \ \& \Rightarrow e2 \geq e1$

Property P3a can be used to check whether, the caregiver's expected personal gain will increase, if the primary stressors of the caregiver decrease. This property succeeded on the simulation traces where the primary stressors of the caregiver indeed decreased.

P3b: Personal gain in agent cg motivates agent cg to provide More Social Support to agent cr.

For all time points $t1$ and $t2$ in trace γ ,
 if at time point $t1$ the level of personal gain of agent cg is $e1$
 and at time point $t2$ the level of personal gain of agent cg is $e2$
 and at $t1$ the level of received support of agent cr is $f1$
 and at time point $t2$ the level of received support of agent cr is $f2$,
 and $e2 \geq e1$, and $t1 < t2$,

then $f2 \geq f1$.

$P3b \equiv \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME} \forall e1, e2, f1, f2: \text{REAL}$

$\text{state}(\gamma, t1) \models \text{expected_personal_gain}(\text{agent}(cg), e1) \ \&$

$$\begin{aligned}
&\text{state}(\gamma, t2) \models \text{expected_personal_gain}(\text{agent}(\text{cg}), e2) \ \& \\
&\text{state}(\gamma, t1) \models \text{received_social_support}(\text{agent}(\text{cr}), f1) \ \& \\
&\text{state}(\gamma, t2) \models \text{received_social_support}(\text{agent}(\text{cr}), f2) \ \& \\
&e2 > e1 \ \& \ t1 < t2 \Rightarrow f2 \geq f1
\end{aligned}$$

Property P3b can be used to check whether the caregiver receives more social support if the expected personal gain of the caregiver increases. This property succeeded on the simulation traces where the expected personal gain indeed increased.

7 Conclusion

The challenge addressed in this paper is to provide a computational model that is capable of simulating the behaviour of an informal caregiver and care recipient in a caregiving process when dealing with negative events. The proposed model is based on several insights from psychology, specifically stress-coping theory, and informal caregiving interactions; see [3] [4]. Simulation traces show interesting patterns that illustrate the relationship between personality attributes, support provision, and support receiving, and the effect on long term stress. A mathematical analysis indicates which types of equilibria occur for the model. Furthermore, using generated simulation traces, the model has been verified against a number of properties describing emerging patterns put forward in the literature. The resulting model can be useful to understand how certain concepts in a societal level (for example; personality attributes) may influence caregivers and recipients while coping with incoming stress. In addition to this, it could be used as a mechanism to develop assistive agents that are capable to support informal caregivers when they are facing stress during a caregiving process. As part of future work, it would be interesting to expand the proposed model in a social network of multiple caregivers and care recipients.

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Chapter 11

An Agent-Based Model for Integrated Contagion and Regulation of Negative Mood

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“All emotions are pure which gather you and lift you up; that emotion is impure which seizes only one side of your being and so distorts you.”

(Rainer M. Rilke)

An Agent-Based Model for Integrated Contagion and Regulation of Negative Mood

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Abstract: Through social interaction, the mood of a person can affect the mood of others. The speed and intensity of such mood contagion can differ, depending on the persons and the type and intensity of their interactions. Especially in close relationships the negative mood of a depressed person can have a serious impact on the moods of the ones close to him or her. For short time durations, contagion may be the main factor determining the mood of a person; however, for longer time durations individuals also apply regulation mechanisms to compensate for too strong deviations of their mood. Computational contagion models usually do not take into account such regulation. This paper introduces an agent-based model that simulates the spread of negative mood amongst a group of agents in a social network, but at the same time integrates elements from Gross' emotion regulation theory, as the individuals' efforts to avoid a negative mood. Simulation experiments under different group settings pointed out that the model is able to produce realistic results, that explain negative mood contagion and emotion regulation behaviours posed in the literature.

Keywords: emotion contagion and regulation, agent-based model.

1 Introduction

There is a wide consensus in sociological literature that human mood spreads through social networks [9, 11]. This social phenomenon is known as contagion. Especially negative moods are strongly influenced by social contacts (e.g., family, friends, colleagues, and neighbours), for example, when the social interaction involves conflict issues or stressful events [4, 15]. Agent-based computational models for contagion of different types of mental states can be found, for example, in [1, 10]. However, in addition to contagion at the social level, also emotion regulation within individuals plays an important role [3]. Emotion regulation is a process through which individuals balance their emotions by exerting forms of control on how they feel [8]. For instance, by avoiding situations or persons who trigger negative emotions, or suppressing anger when receiving bad comments from interviewers. By such emotion regulation mechanisms, persons have the ability to suppress negative influences from interaction with others and maintain a form of emotional homeostasis [7, 8]. For example, if a partner of a depressed person has regulation mechanisms that are strong enough, he or she does not need to become depressed, but if the mechanisms are less strong, there is a serious risk that the partner also becomes depressed.

In recent years, researchers have focused on understanding the mechanisms of emotion regulation, and social contagion separately [2, 13, 15]. However, little information is available to explain how these processes work in an integrated manner by means of computational models. In this paper, an agent-based model is proposed that formalizes and simulates the integrated contagion and regulation of negative mood. In order to exemplify the proposed model, simulation experiments have been performed with a variety of scenarios that include varying personal characteristics and group or network compositions. Attributes were configured, to represent the personality and social characteristics of different individuals. Simulation traces were generated, to show behaviour of these individuals over time, under multiple conditions.

2 Mood Contagion and Regulation

In this section, important ideas and concepts in negative mood contagion and emotion regulation research are addressed. These ideas form the basis of the current computational model that will be formally described in the next section. As described in [5], the degree of mood contagion in groups is influenced by the valence and energy of the mood. One of the fundamental components in mood contagion is the *contagion strength* between individuals within a group [6]. It involves the type of interaction between individuals (*channel strength* from sender to receiver) and personality characteristics of the sender (*expressiveness*) and

receiver (*openness*). For negative mood contagion, channel strength can be defined as the intensity of the social interaction, either via *physical contact* (i.e, face-to-face), or *virtual interaction* (i.e, text message, social networking) [16]. Neighbourhood and personality characteristics, affect the openness for mood contagion of a person [11, 12]. For example, a neurotic individual tends to aggravate negative perception towards incoming mood [14]. In addition to this, a bad neighbourhood (physical or social) also creates a negative influence towards individual's perception in social interaction [12]. Expressiveness is related to the ability of an individual to induce contagion, where an extravert individual can induce a stronger contagion of a negative mood than an introvert individual, because an extravert person expresses his or her internal feelings stronger than an introvert person [1].

Besides mood contagion, emotion regulation plays a role in the experience and transfer of moods. It is important to understand the emotion regulation process, by knowing which different strategies individuals use to exert control over their moods [2]. To serve this purpose, Gross' emotion regulation theory provides a number of strategies to affect individuals' level of emotion [7]. This theory differentiates these strategies into *antecedent-focused strategies* and *response-focused strategies*. The former type of strategies refer to the process preparing for response tendencies before they are (fully) activated, and the latter deal with the actual activation or suppression of the expression of emotional responses [13]. Antecedent-focused strategies can involve the external situation of the person (e.g., avoiding certain places or persons), or the internal processes (e.g., redirecting attention or cognitive interpretation). Gross [7, 8] mentions four examples of antecedent-focused strategies: *situation selection*, *situation modification*, *attentional deployment*, and *cognitive change*. In a response-focused strategy, response modulation is used (e.g., suppressing expressing of negative emotions, or amplifying expression of positive emotions).

Situation selection involves selecting a situation that supports the individual's emotional well-being. This may involve physical and/or social aspects. For example, if a person has a bad response on low light intensity, a form of regulation is to increase this intensity. Especially relevant to the integration with social contagion processes, is the regulation of the social situation. For example, if a person feels bad in a certain social environment, he/she can decrease his/her openness for and intensity of social interaction. Situation modification is similar to selection, but addresses only some aspects of a situation. Attentional deployment includes redirection of attention, for example, on more neutral or positive elements [7]. Cognitive change refers to change in how an individual interprets the situation. Response modulation refers to physical or behavioural actions that decrease the expression of negative emotions [8].

3 The Agent Based Model

The agent-based model introduced in this section combines knowledge on mechanisms for mood contagion and emotion regulation, as briefly introduced above. In this computational model these mechanisms are encapsulated, allowing the simulation of how fragile individuals in their social environment are, towards negative mood contagion. The model describes a process to maintain homeostasis for mood. Through social interaction, there is a habitual tendency of an individual to perceive the negative mood of others and to regulate his or her own moods. Both processes are governed by individual's socio-culture, default (norm) personality, and his or her negative mood. In the formalized model, all nodes are designed to have values ranging from 0 (low) to 1 (high). The interaction will determine the new value for each node, either by a series of accumulations or an instantaneous interaction. To represent these relationships in agent terms, each variable will be coupled with an agent's name (A or B) and a time variable t . The description of these formalizations is described below. For a global overview, see Fig. 1

3.1 Norm Values

Norm values indicate which level each individual is inclined to approximate during the process: an individual tries too keep itself within safe boundaries around these values. These norm values can be seen as a basis for 'default behavioural patterns'; e.g., the openness a person tends to have, based on neighbourhood characteristics and level of neuroticism, or a default level of expressiveness, based on personality characteristics. These norm values are also the natural initial settings of the persons in scenarios. The norm value C_{normAB} at some point in time t for the channel of agent A to agent B , can be related to the amount of physical (PI_{AB}) and virtual (VI_{AB}) interactions that take place, where 0 means no physical or virtual interaction with others, and 1 means a lot of physical interaction [12]. This interaction is regulated by the proportional parameter a . If $a=0.5$, both types of interactions have the same effect, otherwise, one of these types of interactions has more effect on the channel norm value.

$$C_{normAB}(t) = a \cdot PI_{AB}(t) + (1-a) \cdot VI_{AB}(t) \quad (1)$$

Note that the interaction can be bidirectional, so that $C_{normAB}(t) = C_{normBA}(t)$, but this is not assumed to be always the case; the model also covers asymmetric cases, for example, where frequently text messages are sent from A to B but not conversely, or B follows A on Twitter but not the other way around.

Next, the openness norm value O_{normA} of agent A , first relates to the (bad) neighbourhood circumstances of A expressed in a concept NH_A , where a value of 1 means a very 'bad' neighbourhood, which makes a person vulnerable to

negative mood, and the value 0 means the neighbourhood does not make a person more susceptible to negative mood of others. NH_A is modelled as the product of the social (SNH_A) and physical (PNH_A) neighbourhood and of the person. If $PNH_A = 1$, then the physical neighbourhood is very ‘bad’, and it will have a negative effect on the person’s susceptibility. By multiplication of the social and physical neighbourhood in (2), a more ‘positive’ social neighbourhood (with a low value), will make the impact of the ‘bad’ physical neighbourhood smaller [12].

$$NH_A(t) = SNH_A(t).PNH_A(t) \quad (2)$$

The openness norm value O_{normA} of agent A , combines the concepts of a bad neighbourhood NH_A , with the concepts friends ratio NF_A and neuroticism N_A .

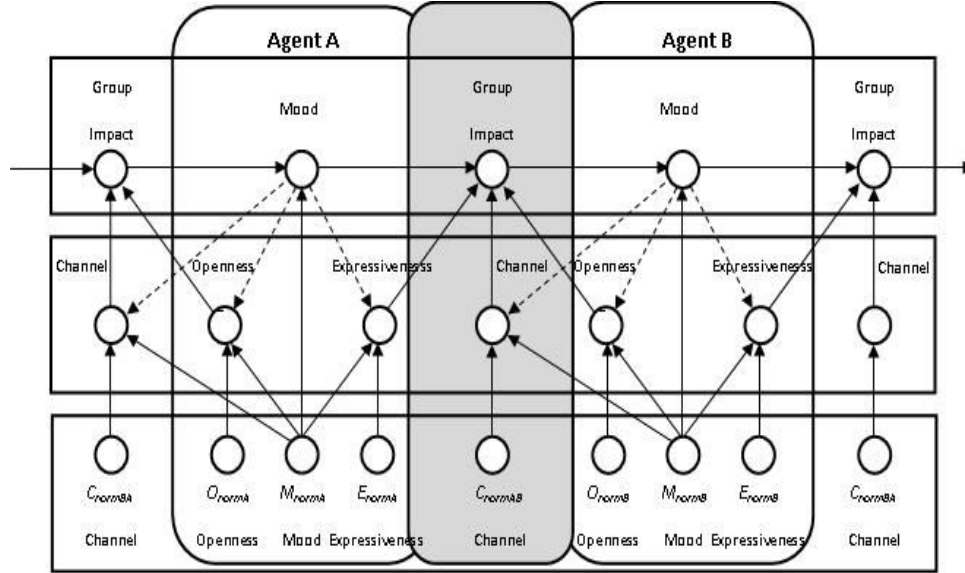


Fig. 1. Overview of the Agent-Based Model Integrating Mood Contagion and Regulation.

In [12] it is described that the more friends you have, the less prone you are to negative mood contagion. The quantity NF_A is defined as a number between 0 and 1 (a ‘friend ratio’): the number of friends is divided by a fixed number (serving as an upper bound) to normalise it. For example, if the upper bound taken is 10 (as in the simulations discussed in Section 4) then one friend will give $NF_A = 0.1$, whereas 7 friends will give $NF_A = 0.7$. Parameter φ regulates the equation; so that it can be modelled which concept can have more effect on the openness norm value than the other. In addition to this, [11] put forward that

the more neurotic you are, the more susceptible you are to negative mood of others. Therefore, the level of neuroticism N_A can amplify or reduce the positive effects of having such as a high number of friends and/or a not bad neighbourhood.

$$O_{normA}(t) = [\varphi.(1-NF_A(t)) + (1-\varphi).NH_A(t)].N_A(t) \quad (3)$$

Finally, in the current model, the expressiveness norm value E_{normA} of agent A is initialised by a number between 0 and 1, not a formula. The number represents the level of expressiveness a person tends to approximate in daily life, where 0 means low expressiveness and 1, high expressiveness.

3.2 The Dynamics of Mood Contagion and Emotional Regulation

In this section the dynamical model for mood contagion and regulation is introduced. A summary of the parameters and state variables of the model is shown in Table 1.

For the mechanisms behind mood contagion, elements from the model presented in [1] have been adopted. The main building block of mood contagion in this model is the contagion strength CS_{AB} from agent A to agent B , where it represents the type and intensity of the contact between agent A and agent B . The higher the value of CS_{AB} , the more contagion will take place.

$$CS_{AB}(t) = E_A(t).C_{AB}(t).O_B(t) \quad \text{where } A \neq B \quad (4)$$

Here, E_A is the personal characteristic expressiveness (the degree in which a person can express his/her mood), C_{AB} the channel strength (intensity of contact, depending on the social relation) from A to B , and O_B the openness (the degree of susceptibility) of the receiver B . Using this equation, the group contagion strength is computed. The group contagion strength $CS_A^*(t)$ towards A is the overall strength by which the negative mood of all other group members is received by A :

$$CS_A^*(t) = \sum_{B \neq A} CS_{BA}(t) \quad (5)$$

Note that for the sake of simplicity here a linear (sum) combination is used. Alternatively, also a logarithmic or logistic combination function might be used. Given the mood levels $M_B(t)$ of the agents $B \neq A$ at time t , the weighted group impact $M_A^*(t)$ of all other agents in the group towards agent A is modelled as:

$$M_A^*(t) = \sum_{B \neq A} CS_{BA}(t).M_B(t) / CS_A^*(t) \quad (6)$$

More details of this model for contagion can be found in [1]. Next the dynamics of the mechanisms for integrated emotion regulation and negative mood contagion are modelled in (7), (8), (9), and (10). The general pattern underlying these dynamical relationships is

$$Y_A(t+\Delta t) = Y_A(t) + \tau \cdot \langle change_expression \rangle \cdot \Delta t$$

Here the change of Y is specified for a time interval between t and $t+\Delta t$; the τ are personal flexibility parameters that represent the speed of the cognitive adjustment processes. Within $\langle change_expression \rangle$ two cases are considered: upward (positive) change $\langle upward_change \rangle$, and downward (negative) change $\langle downward_change \rangle$.

$$\langle change_expression \rangle = (1-Y_A(t)) \cdot \langle upward_change \rangle + Y_A(t) \cdot \langle downward_change \rangle$$

The upward and downward change expressions are determined using the operator $\text{Pos}(x)$ defined as $\text{Pos}(x) = x$ when $x \geq 0$, else 0 .

$$\begin{aligned} \langle upward_change \rangle &= \text{Pos}(\langle basic_change \rangle) \\ \langle downward_change \rangle &= -\text{Pos}(-\langle basic_change \rangle) \end{aligned}$$

Within the basic change expression for (7), (8), and (9), two parts are considered. The first part incorporates the emotion regulation, and the second part the maintenance of homeostasis.

$$\langle basic_change \rangle = \langle regulation_change \rangle + \langle maintenance_change \rangle$$

The latter change expressions were taken linear in the deviation:

$$\begin{aligned} \langle regulation_change \rangle &= \zeta \cdot [M_{norm,A} - M_A(t)] \\ \langle maintenance_change \rangle &= \nu \cdot [Y_{norm,A} - Y_A(t)] \end{aligned}$$

Here ζ and ν are more specific flexibility parameters, for regulation and maintenance. Next it is shown how this general pattern was applied for channel strength (7), openness (8), and expressiveness (9). Firstly, the concepts of emotion regulation are represented in the dynamic adjustment of the strength of the channel from agent A to B . In (7) this occurs by comparing the current mood level to the mood norm value and comparing the current channel level with the channel norm value. These possible deviations influence the adjustment in the strength of the channel that the agent makes. This covers situations in which a person is infected by negative mood from other persons and directs his/her attention away, or physically moves to another place.

$$C_{BA}(t+\Delta t) = C_{BA}(t) + \tau_{CA} [(1 - C_{BA}(t)) \cdot \text{Pos}(\zeta_{CA} [M_{normA} - M_A(t)] + v_{CA} [C_{normBA} - C_{BA}(t)]) - C_{BA}(t) \cdot \text{Pos}(-\zeta_{CA} [M_{normA} - M_A(t)] - v_{CA} [C_{normBA} - C_{BA}(t)])] \cdot \Delta t \quad (7)$$

The dynamic relation for the openness O_A of agent A models another antecedent-focused emotion regulation mechanism [7].

Table 1. Parameters and State Variables of the Model.

Concepts	Formalization
negative mood of agent A	M_A
norm value for the negative mood of agent A	M_{normA}
weighted group impact	M_A^*
expressiveness of agent A (sending side)	E_A
norm value for expressiveness of agent A	E_{normA}
channel strength from agent A to agent B	C_{AB}
norm value for channel from agent A to agent B	C_{normAB}
contagion strength from agent A to agent B	CS_{AB}
overall group contagion strength towards agent A	CS_A^*
openness of agent A (receiving side)	O_A
norm value for openness of agent A	O_{normA}
physical interaction from A to B (face-to-face)	PI_{AB}
virtual interaction from A to B	VI_{AB}
number of friends ‘friend ratio’ of agent A	NF_A
bad neighbourhood of agent A	NH_A
level of neuroticism of agent A	N_A
bad social neighbourhood of A	SNH_A
bad physical neighbourhood of A	PNH_A
proportional parameter for C_{normA}	a
proportional parameter for O_{normA}	φ
flexibility parameter for Y (regulation_change);	ζ_{YA}
flexibility parameter for Y (maintenance_change);	v_{YA}
flexibility parameter of agent A for the re-appraisal emotion regulation in (10)	λ_A
bias of agent A	β_A
flexibility parameter of Y (in a change expression); see (7), (8), (9), (10)	τ_{YA}

$$O_A(t+\Delta t) = O_A(t) + \tau_{O_A} \cdot [(1-O_A(t)) \cdot \text{Pos}(\zeta_{O_A} [M_{norm,A} - M_A(t)] + \nu_{O_A} \cdot [O_{norm,A} - O_A(t)]) - O_A(t) \cdot \text{Pos}(-\zeta_{O_A} \cdot [M_{norm,A} - M_A(t)] - \nu_{O_A} \cdot [O_{norm,A} - O_A(t)])] \cdot \Delta t \quad (8)$$

The expressiveness E_A of agent A involves a response-based emotion regulation mechanism [7, 8]. In (9), expressiveness is adjusted towards the norm value, but also adjusted to decrease expression of negative mood.

$$E_A(t+\Delta t) = E_A(t) + \tau_{E_A} \cdot [(1-E_A(t)) \cdot \text{Pos}(\zeta_{E_A} [M_{norm,A} - M_A(t)] + \nu_{E_A} \cdot [E_{norm,A} - E_A(t)]) - E_A(t) \cdot \text{Pos}(-\zeta_{E_A} \cdot [M_{norm,A} - M_A(t)] - \nu_{E_A} \cdot [E_{norm,A} - E_A(t)])] \cdot \Delta t \quad (9)$$

Finally in (10), an internal antecedent-focused emotion regulation mechanism called re-appraisal [8] is modelled. Here within the generic pattern discussed above the expression $\langle basic_change \rangle$ is instantiated as follows.

$$\begin{aligned} \langle basic_change \rangle &= \langle contagion_change \rangle + \langle reappraisal_change \rangle \\ \text{where} \\ \langle reappraisal_change \rangle &= \lambda_A \cdot [M_{norm,A} - M_A(t)] \\ \langle contagion_change \rangle &= CS_A^*(t) \cdot [\beta_A \cdot (1 - (1 - M_A(t)) \cdot (1 - M_A^*(t))) + (1 - \beta_A) \cdot M_A(t) \cdot M_A^*(t) - M_A(t)] \end{aligned}$$

The latter expression was adopted from [1]. This provides the following mood dynamics relation:

$$M_A(t+\Delta t) = M_A(t) + \tau_{M_A} \cdot [(1-M_A(t)) \cdot \text{Pos}(CS_A^*(t) \cdot [\beta_A \cdot (1 - (1 - M_A(t)) \cdot (1 - M_A^*(t))) + (1 - \beta_A) \cdot M_A(t) \cdot M_A^*(t) - M_A(t)] - \lambda_A \cdot [M_{norm,A} - M_A(t)]) - M_A(t) \cdot \text{Pos}(-CS_A^*(t) \cdot [\beta_A \cdot (1 - (1 - M_A(t)) \cdot (1 - M_A^*(t))) + (1 - \beta_A) \cdot M_A(t) \cdot M_A^*(t) - M_A(t)] + \lambda_A \cdot [M_{norm,A} - M_A(t)])] \cdot \Delta t \quad (10)$$

4 Results

The model was implemented in different numerical software environments, one of which was Matlab. Multiple compositions of groups and networks were simulated, but for the sake of brevity, in this section the simulation scenario with only three agents are considered: namely; (**A**) a ‘depressed’ person with a very negative mood, (**B**) his/her life partner, and (**C**) his/her friend. Through this scenario, it is explored how the negative mood of a person can spread through his/her social network and can be controlled by emotion regulation mechanisms in the receiving persons. For all scenarios, the current simulations used the

following parameters settings; $t_{max}=100$, $\Delta t = 0.1$, flexibility parameters $\tau_{YA} = 0.5$ for *openness*, *channel strength*, *expressiveness*, and 0.1 for negative mood. These settings were obtained from previous systematic experiments to determine the most suitable parameters values in the model. It means, several experiments were conducted to determine how a reasonable time scale and grain size of the simulation could be obtained. In this way, an appropriate setting for the parameters for speed of change, and of the time step Δt was chosen. The other parameters in principle can be chosen in any form as they reflect characteristics of the situation modelled. Table 2 summarizes the (initial) settings for the different agents.

Table 2. Individual Profiles for Each Agent.

	Scenario #1			Scenario # 2			Scenario # 3			Scenario # 4		
	A	B	C	A	B	C	A	B	C	A	B	C
<i>Initial M</i>	0.9	0.4	0.2	0.9	0.4	0.2	0.9	0.4	0.2	0.9	0.4	0.2
M_{norm}	0	0	0	0	0	0	0	0	0	0	0	0
O_{norm}	1	1	1	1	1	1	1	1	1	1	1	1
E_{norm}	1	1	1	1	1	1	1	1	1	1	1	1
C_{norm}	1	1	1	1	1	1	1	1	1	1	1	1
λ	0	0	0	0	1	1	0	0	0	0.5	0.5	0
B	1	0.5	0	1	1	1	0.5	0.5	0.5	1	0.5	0
ν (for all openness O , channels C and expressiveness E)	0	0	0	0	0.1	0.1	0	0	0	0.1	0.1	0
ζ (for all openness O , channels C and expressiveness E)	0	0	0	0.1	0.1	0.1	0	0	0	0.1	0.1	0.1

Scenario # 1

The results of this scenario are shown in Fig. 2. During the simulation, the agent A stays on his negative initial mood. He is not capable of regulating his mood (since he is too depressed; his emotion regulation mechanisms do not work) and transmits his negative mood to his partner and friend.

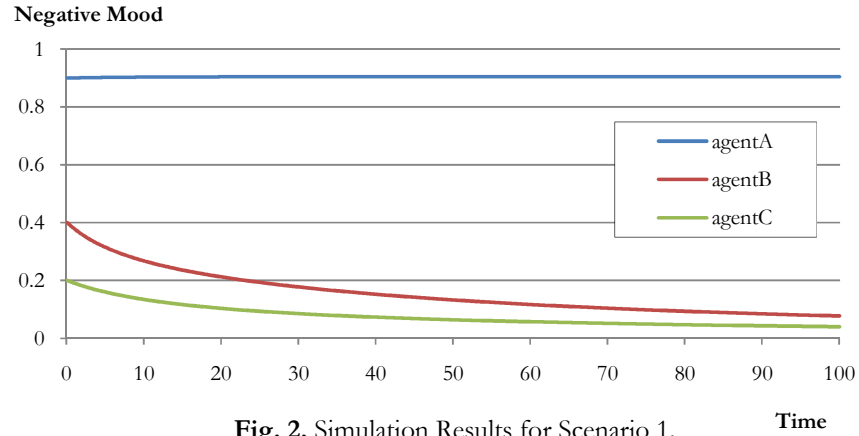


Fig. 2. Simulation Results for Scenario 1.

Because the partner and friend do have intact emotion regulation mechanisms, they are not infected to the level of the ‘depressed’ person’s negative mood. The stronger their emotion regulation mechanisms are, the less the ‘depressed’ person can infect them with his negative mood. Furthermore, agent *B* has a higher negative mood bias ($\beta=0.5$), than agent *A* ($\beta=0$), therefore, agent *B*’s negative mood decreases less fast than for agent *C*.

Scenario # 2

Here all agents have a maximum negative mood bias ($\beta=1$), by which they all approximate the highest initial negative mood (in this case that of the ‘depressed’ person, agent *A*). If no agent would have working emotion regulation capacities, all agents would increase to a negative mood level of 0.9. Now agent *B* and *C* have small emotion regulation capacities and therefore, they do not fully increase to the initial mood level of agent *A*. Fig. 3 depicts the results for this scenario.

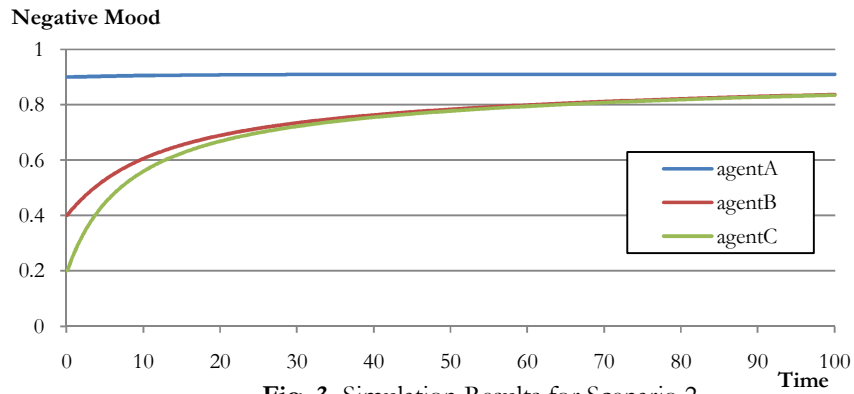


Fig. 3. Simulation Results for Scenario 2.

Scenario #3

This scenario represents the baseline where no emotion regulation mechanisms exist in the three agents. In this case, all agents have a negative mood bias ($\beta = 0.5$), which has the effect that all the agent's mood levels approximate the average initial mood setting (see Fig. 4).

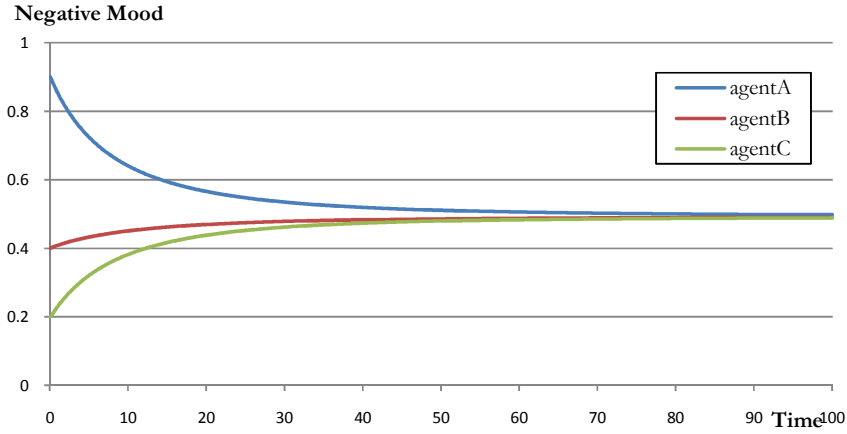


Fig. 4. Simulation Results for Scenario 3.

The emotion regulation mechanisms in agent A and B , let the negative mood levels of agent A and B increase to a lesser extent. As can be seen from Fig. 4, this scenario shows how the negative bias β and emotion regulation mechanism have opposite effects.

Scenario #4

In this scenario, agent C does not have working emotion regulation mechanisms, but agent A and B do. In Fig. 5 it is shown that the emotion regulation mechanisms in agent A and B , let the negative mood levels of agent A and B decrease to a lesser extent, than that of Agent C , compared with scenario 3 (Fig. 5), where no agent had emotion regulation mechanisms that work. This shows how the negative bias β and emotion regulation mechanism have opposite effects: A high negative bias ($\beta > 0.5$) can increase the negative mood of the agent, intact emotion regulation mechanisms (λ_A or ν of openness O , channel strength C or expressiveness E nonzero) will reduce this effect.

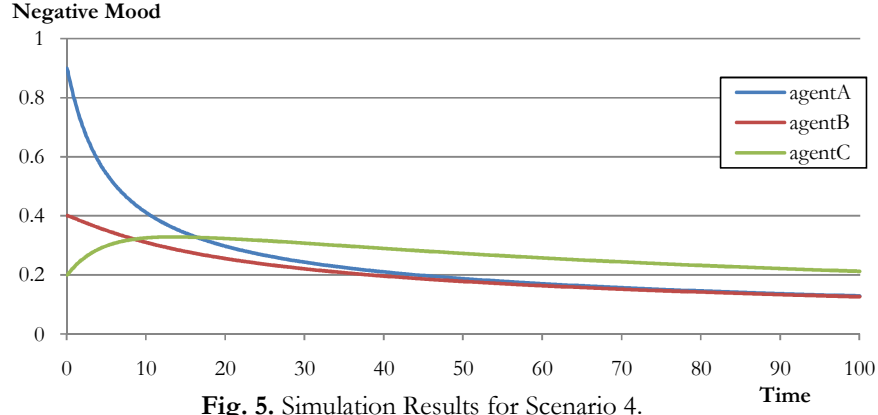


Fig. 5. Simulation Results for Scenario 4.

5 Mathematical Analysis

In this section, an analysis is made of possible equilibria of the model. These are values for the variables of the model for which no change occurs. Taking as a point of departure the generic pattern,

$$Y_A(t+\Delta t) = Y_A(t) + \tau \cdot \langle \text{change_expression} \rangle \cdot \Delta t$$

and assuming τ nonzero, this is equivalent to $\langle \text{change_expression} \rangle = 0$ for all variables Y_A . Moreover, as

$$\begin{aligned} \langle \text{change_expression} \rangle = \\ (1 - Y_A(t)) \cdot \text{Pos}(\langle \text{basic_change} \rangle) - Y_A(t) \cdot \text{Pos}(\neg \langle \text{basic_change} \rangle) \end{aligned}$$

the criterion for an equilibrium is:

$$(1 - Y_A(t)) \cdot \text{Pos}(\langle \text{basic_change} \rangle) - Y_A(t) \cdot \text{Pos}(\neg \langle \text{basic_change} \rangle) = 0$$

Note that always $\text{Pos}(x) = 0$ or $\text{Pos}(\neg x) = 0$; this implies the following lemma:

Lemma 1:

For any nonzero η_1 and η_2 it holds

$$\eta_1 \text{Pos}(x) + \eta_2 \text{Pos}(\neg x) = 0 \quad \text{iff} \quad x = 0.$$

By Lemma 1 it follows that for cases that $Y_A(t)$ is nonzero and < 1 , the equilibrium criterion is

$$\langle \text{basic_change} \rangle = 0$$

If this is applied to dynamic relations (7) to (10) the following four equilibrium equations are obtained:

$$\zeta_{CA} \cdot [M_{normA} - M_A] + v_{CA} \cdot [C_{normBA} - C_{BA}] = 0 \quad (11)$$

$$\zeta_{OA} \cdot [M_{normA} - M_A] + v_{OA} \cdot [O_{normA} - O_A] = 0 \quad (12)$$

$$\zeta_{EA} \cdot [M_{normA} - M_A] + v_{EA} \cdot [E_{normA} - E_A] = 0 \quad (13)$$

$$\beta_A \cdot (1 - (1 - M_A) \cdot (1 - M_A^*)) + (1 - \beta_A) \cdot M_A \cdot M_A^* - M_A + \lambda_A \cdot [M_{normA} - M_A] = 0 \quad (14)$$

The first three equations are equivalent to (here the following short notation is used: $devY = Y_{norm} - Y$ (deviation of Y from norm value)):

$$devC_{BA} = - (\zeta_{CA} / v_{CA}) \cdot devM_A \quad \text{from (11)}$$

$$devO_A = - (\zeta_{OA} / v_{OA}) \cdot devM_A \quad \text{from (12)}$$

$$devE_A = - (\zeta_{EA} / v_{EA}) \cdot devM_A \quad \text{from (13)}$$

In particular, it follows that either none of C_{BA} , O_A , E_A , M_A deviates from its norm, or all of them deviate from their norm (in a proportional manner). For the special case $M_{normA} = 0$ used in the experiments, it holds $devM_A = -M_A$, and therefore the equations are:

$$devC_{BA} = (\zeta_{CA} / v_{CA}) \cdot M_A$$

$$devO_A = (\zeta_{OA} / v_{OA}) \cdot M_A$$

$$devE_A = (\zeta_{EA} / v_{EA}) \cdot M_A$$

Having exploited the first three equations, what remains is the fourth one. To analyse this one, the following lemma is useful.

Lemma 2:

For any A it holds:

$$M_A^* = 0 \quad \text{iff} \quad M_B = 0 \quad \text{for all } B \neq A \text{ with nonzero } CS_{BA}$$

$$M_A^* = 1 \quad \text{iff} \quad M_B = 1 \quad \text{for all } B \neq A \text{ with nonzero } CS_{BA}$$

As the fourth equation is rather complex in its general form, it is analysed for a number of special cases. In particular, assume $\lambda_A = 0$ (no re-appraisal). Then the fourth equation can be rewritten as follows:

$$\begin{aligned} \beta_A \cdot M_A^* - M_A \cdot [1 - \beta_A - M_A^* + 2\beta_A \cdot M_A^*] &= 0 \\ M_A &= \beta_A \cdot M_A^* / [(1 - \beta_A) \cdot (1 - M_A^*) + \beta_A \cdot M_A^*], \\ &\text{if } (1 - \beta_A) \cdot (1 - M_A^*) + \beta_A \cdot M_A^* \neq 0 \end{aligned}$$

For this case, equilibria can occur with values different from 0 and 1, which may depend on the initial values. In addition, three special cases for β_A are considered:

$$\beta_A=0, \beta_A=0.5, \beta_A=1.$$

Case I. $\lambda_A = 0, \beta_A = 0$

In this case the fourth equation can be rewritten into

$$M_A.M_A^* - M_A = 0,$$

which is equivalent to

$$M_A=0 \text{ or } M_A^*=1$$

By Lemma 2 this is equivalent to

$M_A=0$ or $M_B=1$ for all $B \neq A$ with nonzero CS_{BA}
This implies that for this case no equilibria exist with values different from 0 and 1.

Case II. $\lambda_A = 0, \beta_A = 0.5$

In this case the fourth equation can be rewritten into

$$0.5.(M_A+M_A^* - M_A.M_A^*) + 0.5.M_A.M_A^* - M_A = 0,$$

which is equivalent to $M_A = M_A^*$

For this case equilibria can occur with values different from 0 and 1, which may depend on the initial values.

Case III. $\lambda_A = 0, \beta_A = 1$

In this case the fourth equation can be rewritten into

$$M_A - M_A.M_A^* = 0$$

which is equivalent to

$$M_A=1 \text{ or } M_A^*=0$$

By Lemma 2 this is equivalent to

$M_A=$ or $M_B=0$ for all $B \neq A$ with nonzero CS_{BA}
As for Case I, this implies that for this case no equilibria exist with values different from 0 and 1.

6 Discussion

Research into the mechanisms of emotion regulation and social contagion has mainly been conducted separately [2, 13, 15]. In the current work, it was investigated how these processes work in an integrated manner, by means of a computational model. An agent-based model is proposed, that formalizes and simulates the integrated contagion and regulation of negative mood. The current model was inspired by a number of theories, namely emotion contagion and Gross' emotion regulation theory [1, 2, 5, 7]. For short time durations, contagion may be the main factor determining the mood of a person; however, for longer time durations individuals also apply regulation mechanisms to compensate for too strong deviations of their mood. Computational contagion models usually do not take into account such regulation. Simulation results show interesting patterns that illustrate the combined effect of negative mood contagion and emotion regulation. Together, these elements can be used to understand how a person is capable to maintain his or her mood, while maintaining social interactions with another person. For this model, a mathematical analysis shows how such equilibria are indeed possible for the model. Note that for the sake of simplicity mood affecting external events during a simulated process have been left out of consideration. However, it is not difficult to include them too.

In follow up research, more attention will be focused to implement this model in a large scale social networks and to see important emergent behaviours that possibly exist when more agents are involved. Furthermore, it would be interesting to study a situation at a societal level where agents can also change their behaviours (such as relapse, recovery, and susceptibility), by introducing additional attributes and parameters into the model. In addition, this model can be used as a foundation to design software agents that capable to understand and aware about humans and their interactions. By using this model, software agents will use this as knowledge to provide appropriate actions to support humans pertinent to their predicted states (e.g. the level of negative mood). Future work of this model can be extended to incorporate multiple types of emotion and their interaction. Moreover, this model has a potential to be useful to provide a foundation to understand how negative mood can be propagated via social media (e.g., Facebook, MySpace, Twitter).

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Part V

Ambient Agent Models to Support Depressed Persons and their Social Support Networks

Chapter 12

Intelligent Configuration of Support Networks around Depressed People

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“Whoever solves someone else's problem, God will make things easy for him/her in this world and the Hereafter. God is ever assisting His servant as long as that servant is helping anyone in need.”

(Abu Hurairah, Sahih Muslim)

Intelligent Configuration of Support Networks around Depressed People

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Abstract. Helping someone who is depressed can be very important to the depressed person. A number of supportive family members or friends can often make a big difference. This paper addresses how a social support network can be formed, taking the needs of the support recipient and the possibilities of the potential support providers into account. To do so, dynamic models about the preferences and needs of both support providers and support recipients are exploited. The outcome of this is used as input for a configuration process of a support network. In a case study, it is shown how such an intelligently formed network results in a reduced long term stress level.

Keywords: agent-based modeling, configuration, cognitive models, social support networks, unipolar depression.

1 Introduction

Stress is an ever present aspect of life. Long term exposure to stress, often leads to depression [7]. A depression is a mood disorder characterized by a depressed mood, a lack of interest in activities normally enjoyed, fatigue, feelings of worthlessness and guilt, difficulty concentrating and thoughts of death and suicide [4]. If a person experiences the majority of these symptoms for longer than a two-week period they may be diagnosed with major depressive disorder. There has been much recent emphasis on the role of social support network to overcome stress [1, 4]. Social support network refers to the provision of psychological and material resources from the social network, intended to enhance an individual's ability to cope with stress [1]. Essentially, it involves interpersonal transactions or exchanges of resources between at least two persons intended to improve the well-being of the support recipient. From this view, it can promote health through a stress buffering process, by eliminating or reducing effects from stressors.

In this paper it is addressed how a social support network can be formed, taking the needs of the support recipient and the possibilities of the potential support providers into account. This approach can provide a basis for an intelligent application that dynamically suggests support networks based on information available in social network software. The contribution of this paper is twofold. First, an extension of an existing model on preferences for types of social support from the perspective of the recipient (the patient) is presented. The extension describes the process of responding to a request of a specific type from the perspective of the support provider: the social network member that might provide support (Section 2). Second, an approach to use this extended model is proposed for the automated selection of a subset of the patient's social network members that together will provide optimal support (Section 3). In Sections 4 and 5 a fictitious case study is described that illustrates this process. Finally, Section 6 concludes the paper.

2 Dynamic Model of Support Receipt and Provision Process

In this section the support provision and receiving process will be discussed, and a computational model for these processes is presented.

2.1 Important Concepts in Support Receipt and Provision

Before the introduction of the formal model, first the factors will be discussed of the process of giving and receiving support that are important according to the literature. Published studies on this process have usually focused on the perspective of the recipient, provider, and relationship [5]. One of the salient

factors to ensure support can be provided is the request for support. Requests for support may be expressed either *directly* or *indirectly*. Direct request strategies differ from indirect strategies primarily with regard to two inextricably fused aspects; namely, their communicative clearness and their demand characteristics [10]. In this case, personality plays a central role to determine either direct or indirect request is expressed, for example; individuals' with neuroticism to express their request emotional support request through unpleasant emotions gestures. Another important component related to the support recipient factors is the requested support (*need of support*). Support recipients must recognize the need for support and be willing to accept assistance. This factor is influenced by peoples' perceptions of their expectations of others (*perceived the availability of support*) [14].

Types of support needed are highly related with recipients' social tie preference. For example, one reason why individuals may opt for a weak tie support members (e.g: colleague) is that weak ties often provide access to diverse points of information (*informational support*) [10]. In additional to this, researchers have found that health concerns are often difficult topics for people to discuss, especially with interacting with the close tie members. However, other types of support such as *instrumental*, *emotional* and *companionship* are highly related to the strong tie (close friends, family) preference [6]. Another important factor to allow social support is the provider's willingness to help. If the willingness is high, then one is more likely to provide support and vice versa [6, 11]. Provider's willingness is related to the personality attributes and *altruistic* behaviour. The *agreeableness* and highly altruistic individuals contribute to a higher willingness level to help compare those who are not.

2.2 Formal Specifications of Support Recipient and Provision Process

The characteristics of the proposed (extension of the) model are heavily inspired by the research discussed in the previous section on support receipt and provision process. In Figure 1, the states that are depicted in grey represent states that have been modeled in the previous work. The same holds for the dashed lines. Readers interested in these relationships are directed to [2, 3]. In the formalization, all nodes are designed in a way to have values ranging from 0 (low) to 1 (high). To represent these relationships in agent terms, each variable will be coupled with an agent's name (*a* or *b*) and a time variable *t*. When using the agent variable *a*, this refers to the agent's support receipt, and *b* to the agent's support provision.

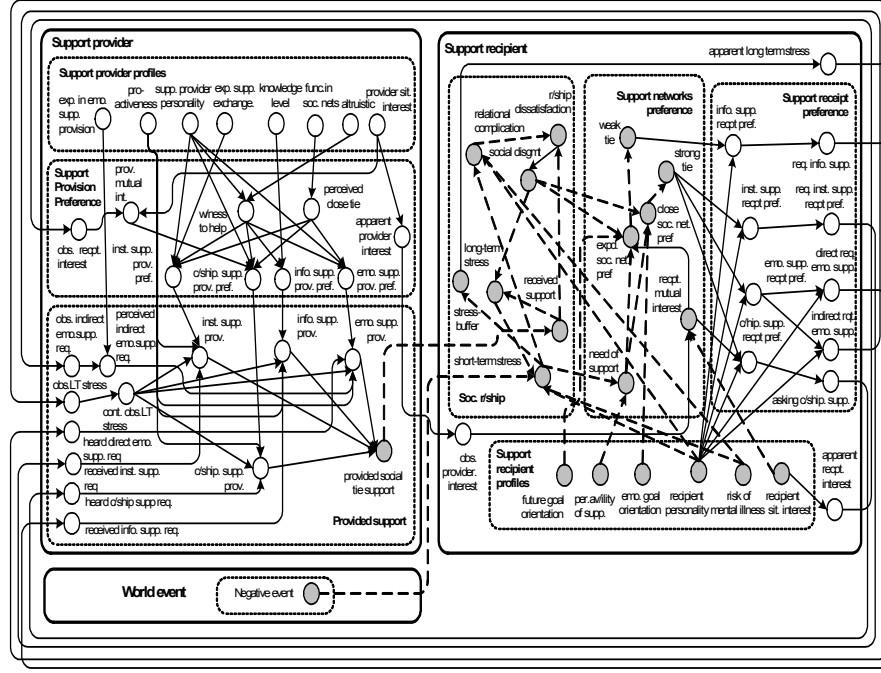


Fig. 1. Global Relationships of Variables Involved in the Support Receipt and Provision Process.

Long Term Stress, and Social Disengagement:

In the model, the world events are generated by simulating potential effects throughout t time. Short-term stress (StS) refers to the combination of negative events, risk in mental illness (vulnerability), and neurotic personality. Related to this, accumulation series of StS will develop the long term stress (LtS). Relational dissatisfaction (RdS) is determined by relational complication when no support is given. Social disengagement (SdG) is primarily contributed the accumulation exposure towards relational dissatisfaction.

$$LtS_a(t+\Delta t) = LtS_a(t) + \eta_{L_s} [Pos(StS_a(t) - LtS_a(t)) \cdot (1 - LtS_a(t)) - Pos(- (StS_a(t) - LtS_a(t)) \cdot StS_a(t))] \cdot \Delta t \quad (1)$$

$$SdG_a(t+\Delta t) = SdG_a(t) + \psi_s (1 - SdG_a(t) \cdot [(RdS_a(t) - SdG_a(t))] \cdot SdG_a(t) \cdot \Delta t \quad (2)$$

Need of Support, Recipient Mutual Interest:

Combination of short term stress (StS) and perceived the availability of support (PvS) triggers the need of support. Recipient mutual interest (RmT) is determined

by number of similar interest between provider (OpI) and recipient (RsI) interest related to n activities.

$$NoS_a(t) = StS_a(t).PnS_a(t) \quad (3)$$

$$RmT_a(t) = \sum sim(RsI_a(t), OpI_a(t)) / n \quad (4)$$

Support Preference (Informational, Instrumental, Emotional, Companionship):

Informational support preference (FrP) is expressed by combining weak tie preference (WsP) and conscientiousness personality (RcS). While, combination of strong tie preference (SsP) with extraversion (ReV) generates instrumental support preference (NrP), and neurotic personality generates emotional support preference (ErP). The value of companionship support preference (CrP) depends by strong tie preference in combination of with the risk in mental illness (RmI), and extraversion personality.

$$FrP_a(t) = WsP_a(t).RcS_a(t) \quad (5)$$

$$NrP_a(t) = SsP_a(t).ReV_a(t) \quad (6)$$

$$ErP_a(t) = SsP_a(t).RnU_a(t) \quad (7)$$

$$CrP_a(t) = [\psi_c.RmI_a(t) + (1-\psi_c).ReV_a(t)].SsP_a \quad (8)$$

Provider Mutual Interest, Willingness to Help:

Provider mutual interest (PmI) is calculated using a similar concept as in recipient mutual interest. Willingness to help (WsH) is modelled by instantaneous relations of agreeableness (PaG) and altruistic (AiC) personality.

$$PmT_b(t) = \sum sim(OrI_b(t), PsI_b(t)) / n \quad (9)$$

$$WsH_b(t) = \Omega_w.PaG_b(t) + (1-\Omega_w).AiC_b(t) \quad (10)$$

Support Provision Preference (Informational, Instrumental, Emotional, Companionship):

All support provision preferences require willingness to help (WsH) in the model, and with its additional attributes. For example, informational provision preference (FsF) needs a knowledge level about the problem (KwL). While, instrumental provision (IsF) is calculated using the combination of agreeableness (PaG), perceived close tie (PcT), and experience in supportive exchange (EsE). Emotional support provision (EsF) depends on perceived close tie, and agreeableness. Finally, companionship support provision (CsF) requires provider mutual interest, perceived close tie, and extraversion personality (PeV).

$$FsF_b(t) = \tau_k.WsH_b(t) + (1-\tau_k).KwL_b(t) \quad (11)$$

$$IsF_b(t) = [\varphi_l.PaG_b(t) + (1-\varphi_l).EsE_b(t)].WsH_b(t).PeT_b(t) \quad (12)$$

$$EsF_b(t) = [\lambda_e.PeT_b(t) + (1-\lambda_e).PaG_b(t)].WsH_b(t) \quad (13)$$

$$CsF_b(t) = [\gamma_c.PmT_b(t) + (1-\gamma_c).PeT_b(t)].PeV_b(t).WsH_b(t) \quad (14)$$

Provided Support:

In general, specific supports (informational (*IfP*), emotional (*EsP*), instrumental (*InP*), and (*CsP*)) can be measured by combining some proportion of proactive effort (*PaC*), and an active observation of long term stress (*AoS*) with particular support preference attributes and support requests (informational (*R/R*), direct emotional (*DeR*), indirect emotional (*PiE*), instrumental (*RnR*), and companionship (*HcR*) support requests). These support requests are combined to model accumulated support (*ApS*), and later, provided support (*PsS*).

$$IfP_b(t) = PaC_b(t).AoS_b(t) + (1-PaC_b(t)).FsF_b(t).RjR_b(t) \quad (15)$$

$$EsP_b(t) = PaC_b(t).AoS_b(t) + (1-PaC_b(t)).[\rho_e.DeR_b(t) + (1-\rho_e).PiE_b(t)].EsF_b(t) \quad (16)$$

$$InP_b(t) = PaC_b(t).AoS_b(t) + (1-PaC_b(t)).IsF_b(t).RnR_b(t) \quad (17)$$

$$CsP_b(t) = PaC_b(t).AoS_b(t) + (1-PaC_b(t)).HcR_b(t).EsF_b(t) \quad (18)$$

$$AoS_b(t+\Delta t) = AoS_b(t) + \lambda_a.[Pos(AoS_b(t) - AoS_b(t)).(1-AoS_b(t)) - (-Pos(AoS_b(t) - AoS_b(t))).AoS_b(t)].\Delta t \quad (19)$$

$$PsS_b(t+\Delta t) = PsS_b(t) + \beta_p.[Pos(f(ApS_b(t)) - PsS_b(t)).(1-PsS_b(t)) - (-Pos(f(ApS_b(t)) - PsS_b(t))).PsS_b(t)].\Delta t \quad (20)$$

where, $f(ApS_b(t))$ is a logistic unit function, $2/(1 + \eta.e^{\alpha(ApS_b(t))}) - 0.5$, and $ApS_b(t) = IfP_b(t) + EsP_b(t) + InP_b(t) + CsP_b(t)$.

The operator Pos for the positive part is defined by $Pos(x) = (x + |x|)/2$, or alternatively; $Pos(x) = x$ if $x \geq 0$ and 0 else. For the similarity function, $sim(.)$ is defined by $sim(x,y) = 1$ if $x=y$ or otherwise 0 .

3 Configuring Social Support Networks

In order to achieve an intelligent assignment of people to a social support network, an approach has been followed in which the dynamic domain model for support receipt-provision process is used as basis for a configuration process. The description of how a domain model can be used to support a person is sometimes called a *support model*. Based on the required support, this support model selects people from an individual's social network and assigns them to the social support network.

3.1 Concepts in the Configuration Approach

Configuration is an application area in Artificial Intelligence that deals with the formation of complex solutions from a set of simpler components. It has been developed in a number of domains, such as manufacturing, medical therapy, industrial plans, personalized marketing ordering, and electronics design [8, 13, 15]. Technically, configuration is the process of creating a technical system from a predefined set of potential objects/components. It begins with broad specifications, and end with in depth specifications of what components are needed and how they are to be arranged [13]. The outcome of such a process has to fulfil a set of given constraints and requirements. Requirements differ from constraints in that constraints must not be violated (*logical consistency*), while requirements must be fulfilled (*logical consequence*) [15]. The configuration itself is performed in an incremental approach, where each step represents a configuration result and possibly includes testing, or simulating with constraint techniques. In general, there are two types of configuration methods namely; 1) *representation-oriented*, and 2) *task-oriented* [15]. The main objective of representation-oriented view is to find the right representation for expressing the structure of the problem domain, while in task-oriented, it focuses to identify the sub-problems to be solved [8]. Several configuration methods such rule-based configuration, dynamic constraint satisfaction problem, and resource-based configuration fall under the group of representation oriented methods. Meanwhile, case based reasoning and hierarchical method can be grouped under task-oriented methods. A detailed discussion on these methods is beyond the scope of this article. Readers interested in those methods will find [13, 15] useful.

3.2 Interaction between Domain and Support Model

There are two fundamental steps in the design of a support model for support provision task assignment. The first is that information about human's states and profiles is fed into a dynamic model of social receipt and provision, which will result in requirements and constraints about the support network. In the second step this will be used to select social support members within the observed social networks. More importantly, this support model will assign support provision task among selected members in line with their resources and preferences. Figure 2 depicts interactions between support model and dynamics model.

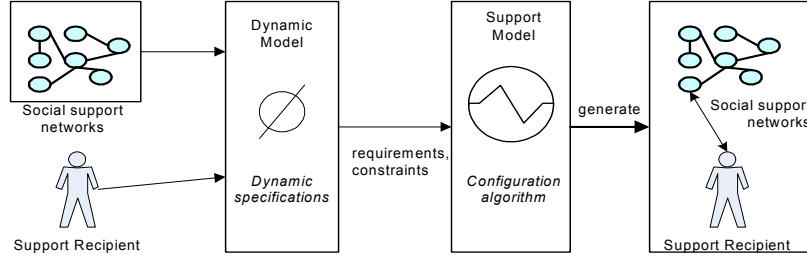


Fig. 2. Interaction between Support and Dynamic Models.

As can be seen in Figure 2, important information of all members in social networks and a potential support recipient will be fed into the dynamic model. Within the dynamic model, instantaneous and temporal relationships will compute both support receipt and provision preferences. Moreover, within the dynamic model, information about support recipient's well-being, such as long-term stress can be monitored. This is crucial as it is a vital indicator when to activate the support model.

In this paper, a resource-based configuration approach is used. This approach assumes that all individual components can be viewed as providing a resource needed in the system. The aim of the configuration model is to select the correct set of support providers based on their ability and the type of support they can provide. The structure of relationships between requested and provided support are not expressed in terms of individual or one-to-one matching, but in terms of their preferences. Therefore, it is possible to describe members providing multiple types of supports and utilizing these preferences. For example, a requirement for a support of 0.3 (on the scale between 0 and 1) can be satisfied by using three support providers with 0.1 amount each.

3.3 A Configuration Algorithm to Assign Support Members

In this paper, the configuration process utilizes support recipient information (from the agent's model) to select support members that available for support provision. The crucial information (*requirements*) needed for a configure process are; 1) tie's preferences, 2) long-term stress, 3) support receipt preferences, 4) function in social networks, and 5) support provision preferences. Using this information with a set of configuration rules, an algorithm to generate a set of social support members to provide support is developed (see Algorithm 1 for details). At the start of this algorithm, a set of constraints, like preference number of providers, percentage of assigned supports, and a level of acceptance burden must be initialized first.

Algorithm 1: Steps in the Configuration Process.

Input: task assignment, number of support provider, acceptable support provider's burden level, and configuration requirements.

Output: A set of selected support providers

Process: Repeat steps S1-S10 until one of the stopping criteria is satisfied.

S1: Check support receipt long term stress and need of help to start the process.

S2: Input task assignment, number of support provider, and acceptable burden level.
Stop if no more task assignment or number of support provider can be assigned

S3: Determine the support network preferences,

$$weak_tie_preference\ (%) = (WsP / (WsP + SsP)).100.$$

$$strong_tie_preference\ (%) = (SsP / (WsP + SsP)).100.$$

S4: Evaluate support receipt preference (requested support).

S5: Assign support provision according to required preferences and tasks equally.
Member with a high support provision will be chosen first, and so forth. If the task assigned or tie preference > the number of support provider, repeat S2.

S6: Assign support providers corresponding to their support provision preferences.

S7: Always assign emotional and companionship support to members in close tie networks if such support resources are still available. Otherwise assign it to another member within weak tie group.

S8: Compute the ratio of provided support over requested support.

$$overall_provided_support(\%) = \Sigma(provided_support) / \Sigma(requested_support).100$$

S9: Evaluate support provider burden. If it exceeds the acceptable burden, repeat S2.

$$burden_provider\ (%) = \Sigma(provided_support) / \Sigma(support_preference).100$$

S10: Evaluate assigned support. If assigned support \geq requested support then construct the list contains the assigned members to provide support, else repeat S2.

Information such as a function in social networks can be used to choose the right support provider. If any individual experiences a heighten long term stress level but do not have any support network preferences, then the agent will have its own autonomy to select suitable individuals for support provision purposes. The expected result from this algorithm is the assignment of social provision tasks for support members in social support networks. Figure 3 summarizes the outcome of this process.

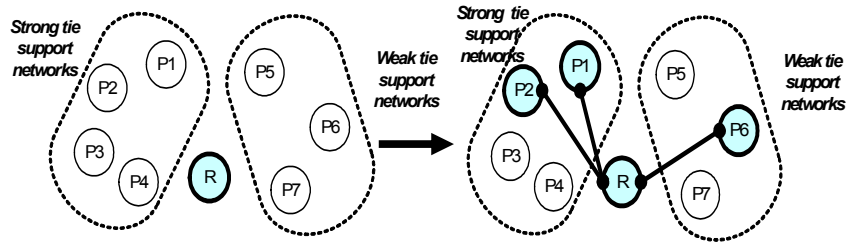


Fig. 3. Social Support Assignment within Social Support Networks.

From Figure 3, consider this example; R requires social support from his/her support networks ($P1, P2, \dots, P6$). To assign support provision task, the support model will extract important information from the domain model, and perform a

configuration process. Based on several pre-determined requirements and constraints, the support model will generate a list contains potential members to provide support. Potential support providers will be selected either from a strong tie network, or a weak tie network, or both networks (in above example, it was from both networks, *P1* and *P2* from the strong tie support networks, and *P6* from the weak tie support networks).

4 Case Study

In this section, a simple case study to show the results of support model is presented. The proposed model has been implemented in visual programming platform by constructing several scenarios to generate simulation traces. For the sake of brevity, only two types of support request and provision will be discussed.

4.1 Support Assignment

In this case study, eleven different fictional persons are studied under several parameters and attributes for social support receipt and provision. Consider this example:

“Piet experiences stress and seeks for help. From his personality and preferences, he needs more informational support (0.7) than companionship support (0.3). What is more, he prefers members from a weak tie network (0.7) to a strong tie network (0.2). Within his social support networks, he has four members in a strong tie and six members in a weak tie network.”

From these members, the support provision availability is the following (*tie network, informational support, companionship support*); **Kees** (*strong, 0.3,0.4*), **Peter** (*strong, 0.1,0.5*), **Anke** (*strong, 0.5,0.5*), **Frieda** (*strong, 0.2, 0.4*), **Jasper** (*weak, 0.5,0.1*), **Bert** (*weak, 0.3, 0.2*), **Johan** (*weak, 0.2, 0.1*), **Sara** (*weak, 0.6,0.2*), **Vincent** (*weak, 0.1, 0.2*), and **Kim** (*weak, 0.2, 0.1*). In this case, three individuals were assigned to provide help. Note that this information is generated from the dynamic model of support receipt and provision process.

Using a support tie preference, he prefers 78 % from support members in a weak tie (≈ 2 members), and 22 % from a strong tie (≈ 1 member). Furthermore, 50 % of provision tasks have been assigned to both members in a weak tie and 100 % for a member in a strong tie. As for the accepted burden level, each individual should not exceed more than 60 % of his/her ability. Based on available information, the algorithm generates this result (see Table 1).

Table 1. Selected Support Provision Members.

Name (strong tie)	Info.	C/ship	Name (weak tie)	Info.	C/ship
Kees	-	-	Jasper	0.25	-
Peter	-	-	Bert	-	-
Anke	0.15	0.3	Vincent	-	-
Frieda	-	-	Sara	0.30	-
			Johan	-	-
			Kim	-	-
Provided support (%)	21 %	100 %		79 %	

From this, support burden is calculated; where Anke will contribute 45 % of her total ability to support, follow by Jasper (42 %), and Sara (38%). If any of these figures exceed the accepted burden level, a new support distribution will be asked. If necessary, the algorithm will select another member to provide support. In this case, Anke will provide 30 % of her preference in informational support, and 60 % in companionship support. Both Jasper and Sara will provide 50 % of their ability to provide informational support to Piet.

4.2 Simulation Results

To analyse the configuration results from our case study, the model presented in Section 2 is used to determine the effect of different variants of support networks. Three conditions have been simulated; namely 1) no support is assigned, 2) random support assignment, and 3) configured support assignment. In the first condition, no support is assigned to help support recipient. As for the second condition, three support members were selected randomly (random numbers were generated to select support members). For the last condition, support members were selected from the list generated by a proposed configuration algorithm. During this simulation, a person (support recipient) has been exposed to an extreme of stressors, to represent the prolonged stressors throughout a life time. The outcomes from these conditions are measured using the individual's long-term stress, and social disengagement levels. These results show selection the right support members have a substantial impact on the course of the long-term stress on support recipient.

For simplicity, the current simulations used the following parameters settings: $t_{\max}=1000$ (to represent a monitoring activity up to 42 days), $\Delta t=0.3$, flexibility rates = 0.3, and regulatory rates = 0.5. These settings were obtained from previous systematic experiments to determine the most suitable parameters values in the model. For all cases, if the long term stress is equal or greater than

0.5, it describes the support recipient is experiencing stress condition. These experimental results will be discussed in detail below.

Results #1: No Support Provided. During this simulation, a person receives no support from its social network. The person experiences very negative events throughout the simulation time. Since the person needs help, but no support has been provided, then a person is unable with the incoming stressors. This results in an increase of the long-term stress. In case the person is more vulnerably towards stress, the long-term stress increases more quickly and therefore it takes more time for the person to recover. For this case, Figure 4(a) shows the effect on social disengagement where it represents a potential risk to isolate from any social interactions. This condition is one of the precursors to develop a depression if no support is given in future [11]. Similar findings can be found in [9, 10].

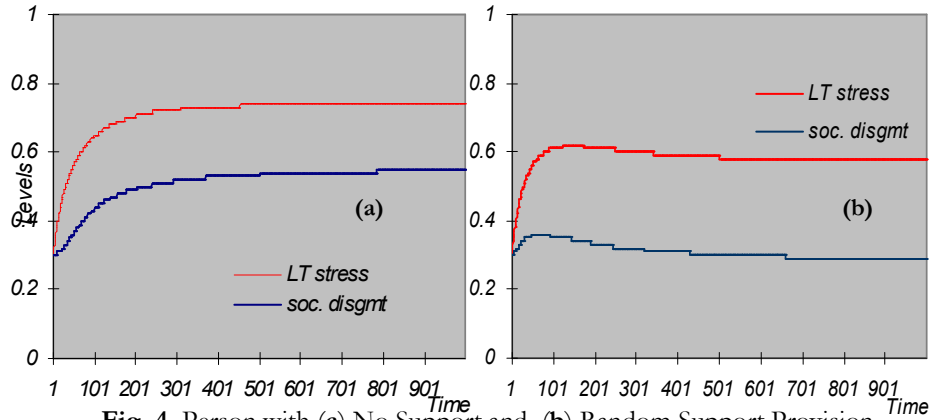


Fig. 4. Person with (a) No Support and (b) Random Support Provision.

Results #2: Random Support Assignment. The analysis of random support assignment helps to understand the effect of support provision assignment without a proper strategy. Figure 4 (b) depicts the effect from this support. As it can be seen in Figure 5, this result provides evidence that by randomly selecting support members is not the best choice if there are many possible variants in support requests and provider's preferences. Although, apparently the long-term stress is decreasing slightly, is not enough to guarantee a person to recover from the incoming stressors. In addition to this, there is a possibility to have a support provider with no support provision preference that matches with the support needed. Thus, a person will have least a chance to recover. On the other hand, if a support provider with the right support preference was chosen, there

is a risk that it might burden the provider [5, 7]. Having this in motion will hamper the effectiveness of support receipt and provision process.

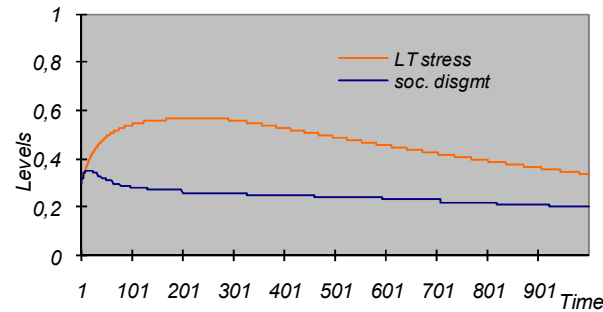


Fig. 5. Person with Configured Support Provision.

Results #3: Configured Support Assignment. In this scenario, a person receives support from suggested support members by the configuration approach. Figure 5 shows a more consistent and gradual decrease in a long-term stress level, compared to the random support assignment. For this scenario, it can be seen that the social disengagement is decreasing, and potentially to show that a person is accepting social support and improving the social interaction within a social support network. This condition occurs almost within the majority of individuals when they received the right support by their support members [4, 10, 11].

5 Conclusion

The case study illustrates that the dynamic model about support provision and receipt together with a configuration algorithm can be used to intelligently form a social support network around persons experiencing stress. The simulations suggest that such an assignment results in a lower long term stress level and a reduced level of social disengagement. Ultimately, this might help people in preventing depression or recovering from a depression. Social networks have always been important in stress reduction, but since social network software (e.g. Facebook, MySpace) has become enormously popular in recent times, it starts to become realistic to think about automating support network formation. Much information about social relations and personal characteristics are available nowadays. For the application of the dynamic models used in this paper, more specific information is needed than what is usually shared via social media. However, it is not unrealistic to envision applications that ask people for such information for specifically this goal of support provision. In future research, it should be investigated which information is essential for an effective formation

of a social support network and whether people are able and willing to provide that information.

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Chapter 13

An Ambient Agent Model for Support of Informal Caregivers during Stress

This chapter is an unpublished paper:

Azizi, A.A., Treur, J., and Wal, C.N. van der. An Ambient Agent Model for Support of Informal Caregivers during Stress.

“Wanneer het op de groten regent, drupt het op de kleinen”
(literally; if it rains on the great, it drips on the little people)

(Dutch proverb)

An Ambient Agent Model for Support of Informal Caregivers during Stress

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Abstract. Caring for a depressed person may have substantial impact on the health and well-being of the caregiver. In this paper, an ambient agent model is proposed that supports caregivers, to prevent or decrease the burden in them and promote their well-being. The agent integrates a domain model of the functioning of the caregiver and the care recipient and their interaction, and exploits model-based reasoning to assess the caregiver's state in order to generate dedicated actions that are tuned to the circumstances.

Keywords: integrative ambient agent model, caregiver stress, informal caregiving interactions, intelligent support for caregivers.

1 Introduction

Ambient Intelligence applications in the health area usually focus on providing support for persons suffering from some disease or mental disorder (e.g., [1]). For the mental health area applications have been designed to monitor and support persons suffering from depression (e.g., [2]). However, often also persons in the daily environment of a depressed person are affected and may experience a heavy burden as an informal caregiver. In the therapeutic area also support for such informal caregivers, such as partners or family members has been developed; see, for example [7]. This paper focuses on these informal caregivers.

An ambient agent model is presented to provide support to caregivers, based on monitoring and assessing the situation of both the caregiver and care recipient, and determining dedicated support actions. The ambient agent model uses a computational model for caregiving interactions, adopted from [3], and exploits model-based reasoning to monitor and assess the situation, and guidelines adopted from [7] in order to generate support actions (based on these assessments) that are tailored to the persons and their states.

In the paper, first in Section 2 the adopted computational (domain) model for caregiving interactions is briefly described. Next, in Section 3 the ambient agent model integrating this domain model is presented. In Section 4 a number of simulation results for different types of scenarios are discussed. Section 5 addresses formal verification of simulation results. Finally, Section 6 is a discussion.

2 A Domain Model for Caregiving Interactions During Stress

In this section, the domain model used is presented. This dynamic model for informal caregiving interactions during stress was adopted from [3]. This model will serve as a basis for later use in an analysis and a support model. Fig. 1 depicts a global description of relevant states within the model and the relations between the states. In the figure, the states that are depicted in grey represent states that have been used as a monitoring component. In addition, the states in bold lines represent the point of impacts of support provided by an intelligent support agent.

Basically, there are three important aspects play vital roles to maintain social support and caregiver's wellbeing, namely; (1) incoming stressors (from the environment (negative events), and care recipient (primary stressor)), (2) mediating conditions (coping, personal attributes), and (3) caregiver outcomes (emotional exhaustion, personal gain, stress, and support provision) [6]. In the model, a number of states have been defined, whereby each state is represented

by a number between 0 (low) and 1 (high). In the previous model, two interconnected models (caregiver and care recipient models) were involved, however for the purpose of this paper, only a caregiver model has been used in a detailed manner, and the recipient model has been used in a more abstracted form. To represent the relationships over time in agent terms, subscripts are used with an agent's name \mathcal{A} (caregiver agent). In addition to this, the current value for all of these temporal relations is related to the previous respective attribute. Note that the change process is measured in a time interval between t and $t+\Delta t$. The operator Pos for the positive part is defined by $\text{Pos}(x) = (x + |x|)/2$, or, alternatively; $\text{Pos}(x) = x$ if $x \geq 0$ and 0 else.

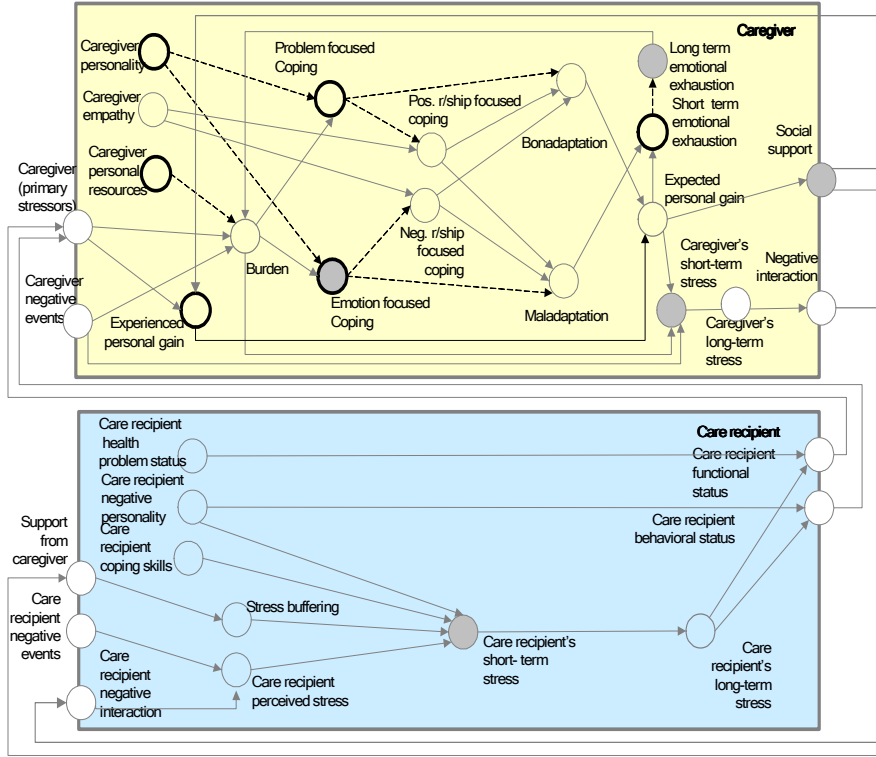


Fig. 1. Overview of the Domain Model for Caregiving Interactions During Stress.

First, the state of burden will be explained. The state *burden* (Bd) is used to express what caregiver feels when dealing with the combinations of *primary stressor* (GpS), *negative events* (NgE), and *emotional exhaustion* (ExH). If the caregiver has adequate personal resources (GpR), it will dampen the progress of burden

level; otherwise it will lead to the formation of *caregiver's short-term stress* (GsS), and later will build up as *caregiver's long-term stress* (GLS).

$$Bd_A(t) = [\beta \cdot GpS_A(t) + (1-\beta) \cdot ExH_A(t)] \cdot (1-GpR_A(t)) \quad (1)$$

$$GsS_A(t) = [\phi \cdot GnE_A(t) + (1-\phi) \cdot Bd_A(t)] \cdot (1-PgN_A(t)) \quad (2)$$

$$GLS_A(t+\Delta t) = GLS_A(t) + \varphi \cdot (GsS_A(t) - GLS_A(t)) \cdot (1-GLS_A(t)) \cdot GLS_A(t) \cdot \Delta t \quad (3)$$

Coping skills (*problem-focused coping* (PfC), and *emotional-focused coping* (EfC)) are influenced by *burden* and *caregiver personality* (GpP). Note that if a person experiences a very high level burden will have the effect that the possibility for him to choose *problem-focused coping* becomes smaller and it is a contrary condition for *emotional focused coping*.

$$PfC_A(t) = GpP_A(t) \cdot (1-Bd_A(t)) \quad (4)$$

$$EfC_A(t) = (1-GpP_A(t)) \cdot Bd_A(t) \quad (5)$$

Positive relationship focused coping (RfC^+) depends on the relation between *problem focused coping* and *caregiver's empathy* (GE). A high empathy will increase this function, while reducing its counterpart (*negative relationship focused coping* (RfC^-)). Other important state is a condition where either caregiver meets the need of caregiving outcome (*bonadaptation*) or otherwise (*maladaptation*). *Bonadaptation* (Bn) is related to the high personal accomplishment (*expected personal gain* (PgN)), and *provided support* (ScP). *Maladaptation* (Md) is linked to the development of *short-term exhaustion* (EsH), while *expected personal gain* will reduce this effect.

$$RfC_A^+ = PfC_A(t) \cdot GE_A(t) \quad (6)$$

$$RfC_A^- = EfC_A(t) \cdot (1-GE_A(t)) \quad (7)$$

$$Md_A(t) = [Y \cdot RfC_A^-(t) + (1-Y) \cdot EfC_A(t)] \cdot (1-RfC_A^+(t)) \quad (8)$$

$$Bn_A(t) = [\rho \cdot RfC_A^+(t) + (1-\rho) \cdot PfC_A(t)] \cdot (1-RfC_A^-(t)) \quad (9)$$

$$EsH_A(t) = Md_A(t) \cdot (1-PgN_A(t)) \quad (10)$$

Experienced personal gain (EpN) can be measured by comparing the level of provided support, and the effect of that support towards well-being of the care recipient. Finally, consistent exposure of short-term exhaustion will increase the level of *long-term emotional exhaustion*.

$$EpN_A(t+\Delta t) = EpN_A(t) + \mathfrak{A} \cdot [Pos((ScP_A(t) - GpS_A(t)) - EpN_A(t)) \cdot (1 - EpN_A(t)) - Pos(-(ScP_A(t) - GpS_A(t)) - EpN_A(t)) \cdot EpN_A(t)] \cdot \Delta t \quad (11)$$

$$ExH_A(t+\Delta t) = ExH_A(t) + \gamma \cdot [Pos(EsH_A(t) - ExH_A(t)) \cdot (1 - ExH_A(t)) - Pos(-(EsH_A(t) - ExH_A(t)) \cdot ExH_A(t))] \cdot \Delta t \quad (12)$$

Parameters ϕ , β , \mathcal{I} , and ρ provide a proportional contribution factor in all respective instantaneous specifications. Furthermore, the rate of change for all temporal specifications are determined by flexibility rates, γ , \mathcal{Q} , ϕ , and ψ , respectively.

3 The Integrative Ambient Agent Model

After the discussion of the domain model, this section focuses on the integrative ambient agent model used to support caregivers. A basic element in the ambient agent model is the integration of domain model within it. By incorporating the domain model, an ambient agent gets an understanding of the processes of its environment [1], [2]. Basically, there are two different ways to integrate a domain model within agent model [4]. First, the domain model is used as a basis to perform analysis of the human's states and processes by reasoning on observations and specific sensors (analysis model). Second, the domain model is used as a foundation to provide support for the human (support model). These two models are used within the two corresponding components within the ambient agent model. Fig. 2 (dotted arrows, left hand side) shows these two types of integration of the domain model in the ambient agent model. A third way of using the domain model is as an agent model to simulate human behaviour in order to test the ambient agent model (dotted arrow in Fig. 2, right hand side).

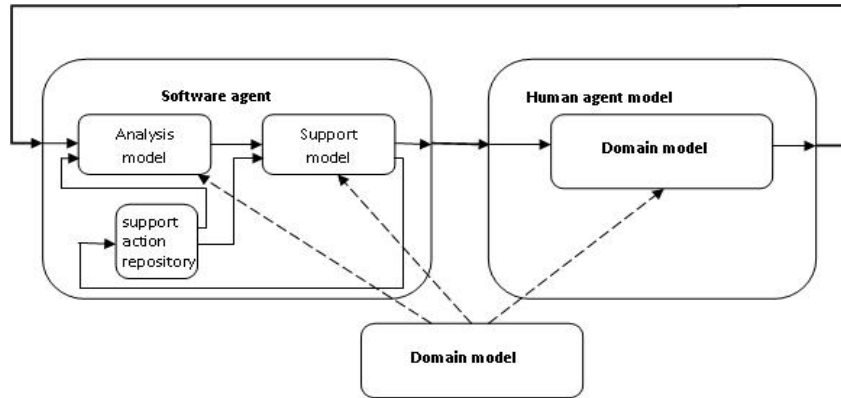


Fig. 2. The Integration of a Domain Model Within an Agent Model.

In Fig. 2, the solid arrows indicate information exchange between processes. In the ambient agent model, another component is introduced, namely a support action repository. This additional component keeps track of the generated support actions given by the ambient agent to the caregiver. Note that there two incoming arrows to the analysis component. The first arrow provides

information about the environment (care recipient stress, personality and resources), the second arrow provides information about already provided support to the caregiver (from the support action repository). The outcome of the analysis component has the form of assessments, and is used as input for the support component, another incoming arrow for the support component provides the already selected support actions and their frequency from the support action repository. The outgoing arrows from the support component define provided support actions to the caregiver, and support action repository. The support action repository will update the frequency of provided support action from this information. In the next section, the details of the analysis and support component will be discussed.

3.1 The Analysis Component

First the analysis component is addresses; see Fig. 3. To be able to analyse the dynamics of the caregiver's and care-recipient's conditions, an ambient agent should be equipped with a domain model such as the one introduced in Section 2. Based on this knowledge, the ambient agent is able to have some understanding of the human processes and actions.

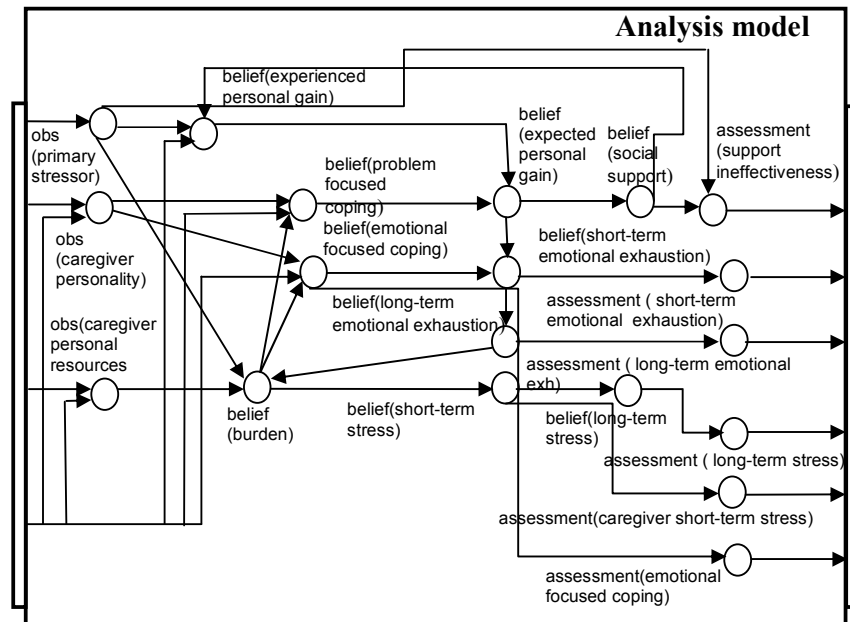


Fig. 3. Overview of the Analysis Model for the Caregiving Processes.

Hence, the model for analysis in principle should include approximately the equivalent concepts as in the domain model. Note that not all concepts that exist in the domain model can be physically observed by the ambient agent [4]. For example, the level of ‘experienced personal gain’ is not something that is explicitly observable in the real world. To overcome this issue, the agent approximates values for such nonobservable variables by using beliefs derived using the integrated domain model. To capture important essences in analyzing caregivers’ states, the following concepts are needed: (1) observations of primary stressors, caregiver personality and personal resources, (2) beliefs in (problem and emotional focused) coping characteristics, (3) beliefs in emotional exhaustion (short and long term), (4) beliefs in burden, (5) beliefs in experienced and expected personal gain, (6) beliefs in stress (short and long term), and (7) beliefs in social support.

As can be seen, these concepts are similar to the concepts explained in Section 2, but as a form of integration embedded in observations or beliefs. For example, the concept of belief about an value V at time t for the variable of the domain model named as `long_term_stress` is used in the analysis component as `belief(long_term_stress, V, t)`. Using these embeddings of domain concepts, the ambient agent model is able to assess a caregiver’s conditions and provide this information as inputs to the support component, using dynamical relations between such beliefs based on the corresponding dynamical relations in the domain model. For example, suppose in the domain model the following relation is given specifying how state variable y depends on state variables x_1, x_2, x_3 :

$$y(t+\Delta t) = y(t) + f(x_1(t), x_2(t), x_3(t))\Delta t$$

Then this is integrated in the analysis model as:

$$\begin{aligned} &\text{belief}(x_1, V_1, t) \wedge \text{belief}(x_1, V_2, t) \wedge \text{belief}(x_3, V_3, t) \\ &\rightarrow \text{belief}(y, f(V_1, V_2, V_3), t+\Delta t) \end{aligned}$$

where \rightarrow denotes a temporal causal relation

Fig. 3 provides an overview of such dynamical relations in the analysis model. Note that for simplicity of notation here the values of the states are not mentioned.

3.2 The Support Component

The support model (see Fig. 4) can be specified in two different manners. First, the ambient agent can select support based on a rule-based approach using the following representation:

$$\begin{aligned}
& \text{assessment}(x_1, V_1) \wedge V_1 > \text{threshold_assessment_1} \wedge \\
& \dots \\
& \text{assessment}(x_k, V_k) \wedge V_k > \text{threshold_assessment_k} \wedge \\
& \text{frequency_provided_support_A} < \text{threshold_frequency_support_A} \\
& \rightarrow \text{support_action}(a_1)
\end{aligned}$$

Here x_1, \dots, x_k represent the assessed conditions, V_1, \dots, V_k represent observed or estimated values, and a_1 represents a support action.

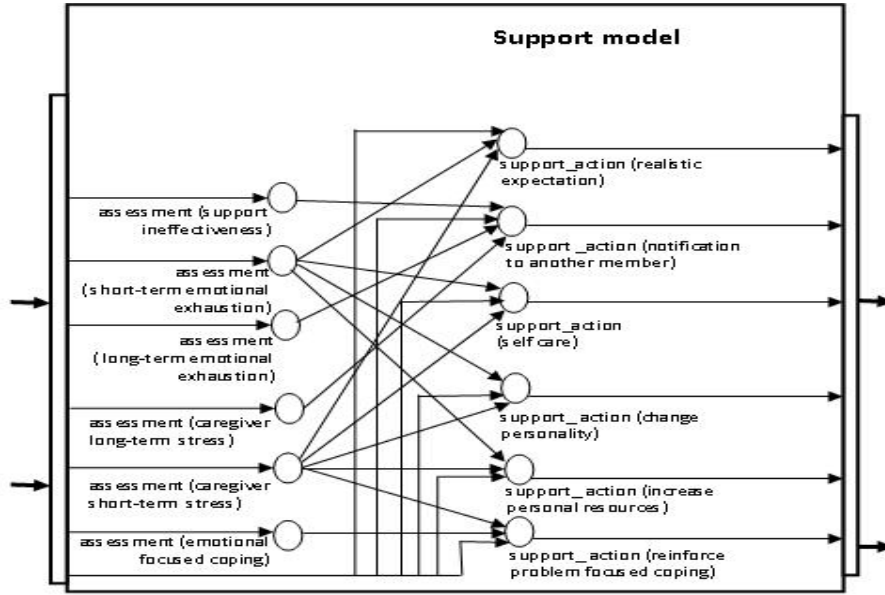


Fig. 4. Overview of the Support Model for a Caregiver.

From this representation, the ambient agent will activate support that match the conditions expressed in the antecedents. Note that all threshold values can be specified by a user. The frequency of provided support can be obtained from the action repository, and aims to discontinue from providing a specific support if the caregiver shows no improvement after previously receiving the same support. It provides a mechanism to diversify support provided by an ambient agent.

Another approach to specify a support model is in a numerical manner, using the weighted networks. For this approach, each support action (e.g., a_i) will receive a summation of weighted input (y) from a set of selected assessments (x_i). For this, a form of continuous logistic function can be used, as in [14].

$$y(t) = \sum_i x_i \cdot w_i \quad (13)$$

$$f(t) = \left(\frac{1}{1 + e^{-\sigma(y(t) - \tau)}} - \frac{1}{1 + e^{\sigma\tau}} \right) \cdot (1 + e^{-\sigma\tau}) \quad (14)$$

where w is a weight vector, σ is a steepness and τ a threshold parameter. In this choice, a common practise is followed (logistic function) but other types of combination functions can be specified as well. For this approach, the connection between the agent's assessment results and support actions can be represented as follows:

$$\text{assesment}(x_1, V_1) \wedge \dots \wedge \text{assesment}(x_k, V_k) \rightarrow \text{support_action}(a_1, f(V_1, \dots, V_k))$$

where $f(\cdot)$ represents a combination function.

Results from the continuous logistic function will be evaluated, where a support action with the highest value will be chosen. However, to allow agent's flexibility in providing support, users can choose more support actions with second or third highest values. The details of the support component can be found in Section 4. Fig. 4 shows the relationship between results from an analysis component (assessments) and support actions.

4 Concepts and Effects in Support for Informal Caregivers

This section explains how the proposed model incorporates characteristics of effective treatments for family caregivers in general and those specific to caregivers of depressed people. By specifying these characteristics of effective treatments for caregivers, the proposed model should be as effective as possible to current standards and knowledge.

4.1 Important Concepts in a Support Model

Zarit and Femia [15] describe four characteristics of effective treatments for caregivers: a psychological approach, multidimensionality, flexibility and sufficiency. The psychological approach refers to practicing new skills and behaviours by caregivers in a group or one-to-one interventions with a psychotherapist. Multidimensional interventions are interventions that address multiple stressors and risk factors that affect the caregiver, instead of just one stressor or risk factor. Flexibility means that an effective treatment is flexible in its set up: it should not be a scripted protocol intervention, but the intervention should be adjustable to the needs of the caregiver [11]. Sufficiency can refer to provision of ongoing support to caregivers, for example, by ongoing support groups, follow-up sessions of an intervention. These four characteristics have

been integrated in the proposed support model for family caregivers of depressed people as follows:

The psychological approach can be found in the indirect referral to support groups by the ambient agent and in the direct support actions of ‘reinforce problem focused coping’, ‘realistic expectations’ and ‘increase personal resources caregiver’. The supportive actions are set up in a way that the caregiver is instructed, how to apply general theories to his/her own specific situation and motivated to make plans how to implement these new skills. The ambient agent also gives the caregiver feedback on how he/she is implementing the new skills. The proposed model is also multidimensional, in that it focuses on many possible stressors and risk factors of the caregiver (personality, finances, coping skills, thinking skills, own health). Flexibility in the proposed model can be found in the continuous monitoring of the caregiver by the ambient agent and therefore continuous adjustment of the intervention to the needs of the caregiver. Finally, sufficiency is also integrated in the proposed model by providing ongoing support to the caregiver. Sufficiency and flexibility are the main advantages of the proposed model. The multidimensionality and psychological approach are still open for improvement, by new insights from research.

Next, it is explained how characteristics of treatments, specially, for caregivers of depressed people were integrated into the proposed model. Cuijpers [7] describes an intervention specific for family caregivers of depressed people, based on his experience with depressed patients and with their family caregivers. There are eight ways for caregivers to deal with the depressed person they care for, which are shown (translated from Dutch) in Fig. 5.

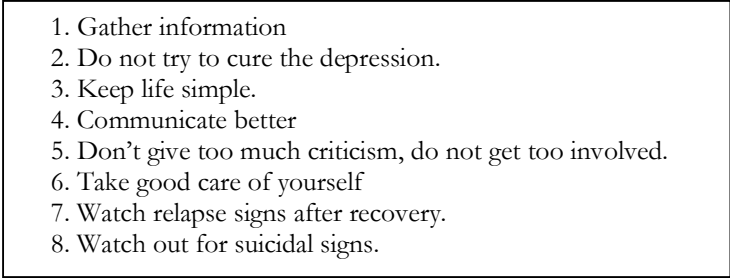
- 
1. Gather information
 2. Do not try to cure the depression.
 3. Keep life simple.
 4. Communicate better
 5. Don't give too much criticism, do not get too involved.
 6. Take good care of yourself
 7. Watch relapse signs after recovery.
 8. Watch out for suicidal signs.

Fig. 5. Eight Steps in the Intervention of Family Caregivers of Depressed People.

These eight steps are integrated in the proposed model, as well as the seven ways as Cuijpers describes to relieve the burden or stress experienced by the caregiver, shown in Fig. 6, (translated from Dutch) [6].

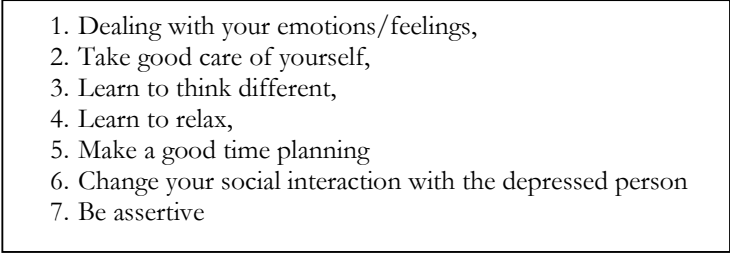
- 
1. Dealing with your emotions/feelings,
 2. Take good care of yourself,
 3. Learn to think different,
 4. Learn to relax,
 5. Make a good time planning
 6. Change your social interaction with the depressed person
 7. Be assertive

Fig. 6. Seven Ways to Relieve the Burden or Stress Experienced by the Caregiver.

The current support model consists of multiple supportive actions advised by the ambient agent to the caregiver. The first support action is called “increase personal resources caregiver”. This support action is aimed at teaching the caregiver to manage stress, which will decrease the burden. Examples are teaching the caregiver to make a to-do list and becoming more assertive, like in points 5 and 7 in Fig. 5. This will affect the caregiver’s personality (as in changing his/her stress reactions: now he/she gets well organised, and more assertive) and the caregiver’s social and financial resources (as in getting financial/practical help from friends/family).

The second support action is called “reinforce problem focused coping caregiver”. Here the ambient agent teaches the caregiver how to learn to apply problem focused coping instead of emotion focused coping and gives feedback. Research shows that coping is a learnt behaviour, see a review in: [13]. Examples are: text messages or instruction movies on phone/through emails, in which it is shown how to deal in certain situations or dialogues with the depressed person. Also the ambient agent will ask to plan and report the new skills the caregiver has to apply, so it can monitor the newly developed skills and give feedback to the caregiver. This support action decreases the caregiver’s emotion focused coping and increases the caregiver’s problem focused coping: increases. These skills fall under points 2-5 in Fig. 5 and 1,3,6,7 in Fig. 6.

The third and fourth support actions are called “realistic expectations and self-care caregiver”. In these actions, the ambient agent gives information about the illness so the caregiver gets an understanding of the behavioural patterns and needs of the depressed person (corresponding to point 1, Fig. 5). Also the ambient agent teaches the caregiver to take care of him/herself (physically, emotionally, and mentally) and asks for reports and plans and gives feedback (points 6 Fig. 5, points 2, 4, Fig. 6). Examples are: text messages or movies on phone/through emails, in which examples of the behaviours of other depressed persons are given, like how fast they recover or relapse. Giving tips in self-care,

like taking a time-out, finding social support, eating healthy, exercising regularly and learning relaxation exercises. These support actions increase the caregiver's experienced personal gain, because the caregiver will experience less disappointments since the caregiver learns to have more realistic expectations towards the depressed person [10]. The caregiver's short term emotion exhaustion will also decrease.

The fifth support action is aimed at other persons than the 'main' informal caregiver, namely other (possible) caregivers, friends of the 'main' caregiver, or a specialist like a doctor or therapist. The fifth support action is called: "giving warning" and refers to the ambient agent giving information to another person than the caregiver it is supporting. This information contains a warning signal that the depressed person and the caregiver both need support from others. The effect of support from an ambient agent to the caregiver will be dealt in the next section.

4.2 Dynamics Specifications of the Effects from a Support Model

Previously, several important concepts of agent's supports were introduced. Using those concepts, it is possible to specify computational properties to visualize the effects from the support provided by a support agent. The dynamic specifications of an agent-based support can be structured pertinent to the purposes of the support, namely; (1) to reduce long-term exhaustion in a caregiving process, (2) to develop problem-focused coping skills, and (3) to improve personality attributes that reduce the physiological signs of stress [6][8][13]. The asterisk sign (*) is used to represent the extended equations about the effect of the supports towards a caregiver's processes.

Support to reduce long-term emotional exhaustion. In this case, the support agent aims to reduce further negative influences that cause emotional exhaustion. From Table 1, the support agent will provide important advices and suggestions to regulate self-care to increase external personal resources, and to foster more realistic expectations. The effect of short-term emotional exhaustion after following agent's support is estimated after adding a new support parameter, δ_{SA} and a self-care effect into the original equation (Equation (10)). This indicates that when self-care, $Sc(t) \rightarrow 1$ and $\delta_{SA} \rightarrow 1$, then the short-term emotional exhaustion is reduced to zero. Another important effect after following the support is having more external personal resources. Thus, a new caregiver personal resource (GgR^*) can be expressed as having a combination of existing resources (GpR) and external resources (Ep).

$$EsH^*_{SA}(t) = Md_A(t) \cdot (1 - PgN_A(t)) \cdot (1 - \delta_{SA} \cdot Sc(t)) \quad (15)$$

$$GgR^*_{SA}(t) = \delta_{EA} \cdot GpR_A(t) + (1 - \delta_{EA}) \cdot Ep(t) \quad (16)$$

The new value of experienced personal gain depends on a combination of the previous equation in (11) and support contribution when a person is capable to achieve realistic expectations (Re).

$$EpN^*_{A(t+\Delta t)} = EpN_A(t) + \mathcal{G}(\delta_{RA} \cdot [(Pos((Sip_A(t) - GpS_A(t)) - EpN_A(t)) \cdot (1 - EpN_A(t))) - Pos((Sip_A(t) - GpS_A(t)) - EpN_A(t), EpN_A(t))] + (1 - \delta_{RA}) \cdot Re(t) \cdot (1 - EpN_A(t)) \Delta t \quad (17)$$

Support to reduce dependency on emotional-focused coping skills: In order to visualize the effect when a person follows agent's advices to reinforce problem-focused skills, both new problem-focused and emotional-focused coping skills are calculated as follows:

$$PfC^*_{A(t)} = GpP_A(t) \cdot (1 - ((1 - \delta_{EA}) \cdot Rp(t)) \cdot Bd_A(t)) \quad (18)$$

$$EfC^*_{A(t)} = (1 - GpP_A(t)) \cdot Bd_A(t) \cdot (1 - \delta_{EA}) \cdot Rp(t) \quad (19)$$

where δ_{EA} determines the influence of the acceptance in change coping skills and Rp represents reinforce problem focused coping skills.

Support to reduce physiological signs of stress: For this type of support, changes in both caregiver personality and resources are needed. In this case, a new caregiver personality (GpP^*) is calculated by combining the existing personality, and the positive personality (Cp) from the support. Equation (14) provides similar effect for the new caregiver resources.

$$GpP^*_{A(t)} = \delta_{PA} \cdot GpP_A(t) + (1 - \delta_{PA}) \cdot Cp(t) \quad (20)$$

In addition to this, δ_{EA} , δ_{RA} and δ_{PA} are support-acceptance parameters; it represents a person's ability to accept respective changes from the support.

5 Some of the Simulation Results

The ambient agent model presented in Section 3, integrating the domain model as described in Section 2 was implemented in Matlab in order to perform simulation experiments. For the simulations, the functioning of the designed system was explored in interaction with three fictional types of caregivers (caregiver 1 (CG1), caregiver 2 (CG2), and caregiver 3 (CG3)). Both caregivers (1 and 2) are ineffective caregivers and susceptible for long-term stress in a caregiving process (low in positive personality and resources), while caregiver 3 is an effective caregiver. In this case, caregiver 1 ignores the support provided by

the intelligent support agent, and caregiver 2 follows the support. In addition to this, information about the care-recipient's (CR) stress buffer and long-term stress has been used to measure the outcome of the agent support (as in [2]). The care-recipient stress buffer represents a process of support protecting the care recipient from potentially adverse effects of stressful events (stressors). Therefore, many studies have shown that a high stress-buffer level will reduce the development of care recipient long-term stress level in future [6][9]. In this simulation, our care recipient is experiencing negative events (stressors) and expects supports from a caregiver (also facing incoming stressors).

Table 1. Initial Values for the Simulation Experiments.

	Caregiver 1 (CG1)	Caregiver 2 (CG2)	Caregiver 3 (CG3)	Care recipient (CR)
CG personality	0.2	0.1	0.8	-
CG personal resources	0.2	0.1	0.7	-
CG empathy	0.3	0.3	0.7	-
CR personality	-	-	-	0.3
CR coping skills	-	-	-	0.1

These conditions are chosen to show the effect of different effects on the long-term stress, emotional exhaustion, provided support, and on the influences of the support. In addition to this, there are several parameters that can be varied to simulate different characteristics. However, in this simulation, we used the following settings: $t_{\max} = 1000$ (to represent a monitoring activity up to 42 days), $\Delta t = 0.3$, regulatory rates = 0.5, flexibility rates = 0.2, and support-acceptance rates = 0.3. These settings were obtained from several experiments to determine the most suitable parameter values for the model. In addition, the weighted network is implemented in the support model to select the most appropriate support. To illustrate the effect of support, all caregivers receive support by the agent after half of the simulation period.

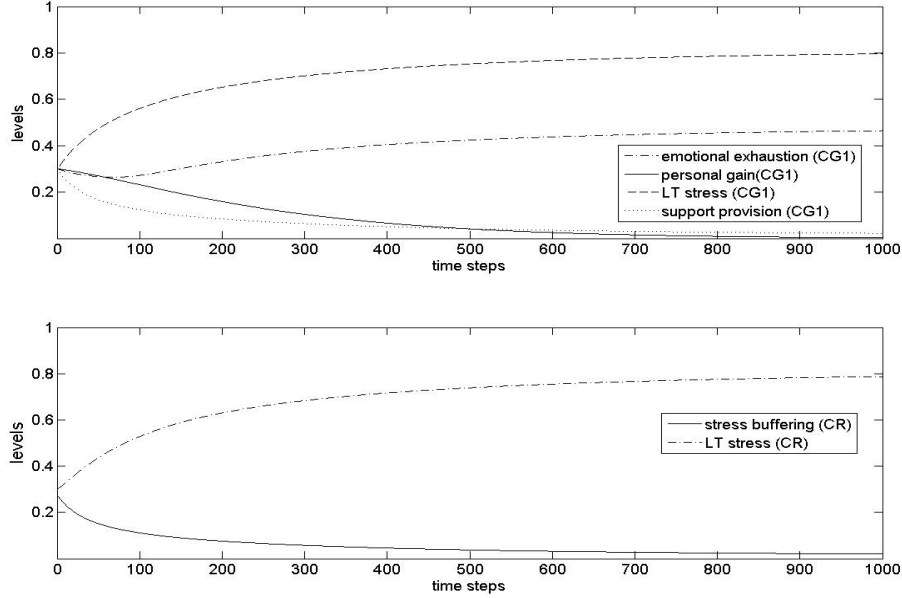


Fig. 7. An Ineffective Caregiver (CG1) without Support, and a Bad Care Recipient (CR).

Fig. 7 visualizes a condition when the caregiver is avoiding the agent's support while facing intense stressors. Facing such events, both persons (CG1 and CR) are facing high long-term stress levels and emotional exhaustion in the long run. As a result, the caregiver is experiencing a low personal gain and support provision, which later lower the effect of stress buffering in care recipient. This condition occurs when a caregiver feel burden by the caregiving activities [12]. Eventually, without any support, both caregiver and care recipient will have a higher possibility to get depressed.

However, in Fig. 8 different scenarios can be seen when an ineffective caregiver does follow the provided support from a support agent. After following the recommended advices, the caregiver improves his / her ability to provide support. One of the precursors to explain this outcome is the increasing caregiver's personal gain. It is consistent with the findings that suggest that caregiving satisfaction encourages a caregiver to provide more support [10][12]. In addition to this, by following the specific advices, the caregiver is helped to apply more focused-coping skills, which later on influence the development of positive relationship focused coping. In many reports in the literature, problem-focused coping skills give a positive outcome in a caregiving process, for both caregiver and care recipient.

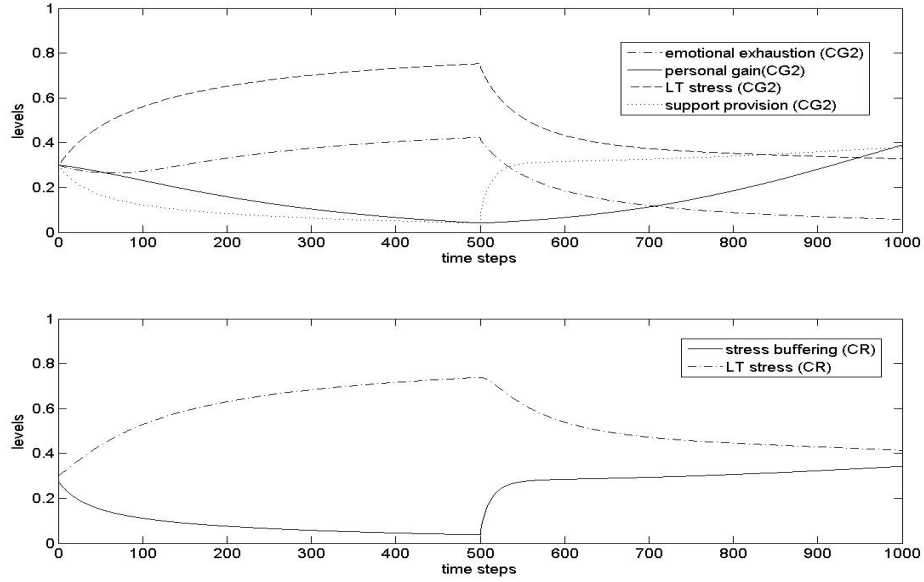


Fig. 8. An Ineffective Caregiver (CG2) with Support, and a Bad Care Recipient (CR).

In another case (see Fig. 9), an effective caregiver requires no support from the support agent since he/she is capable to provide adequate support during the caregiving process. It is obvious to see that caregivers with more positive personality, personal resources and empathy tend to provide better support compare to those who are not [11][13]. This results in an increase of the stress buffering level, and later will dampen the development of the caregiver's long-term stress. Another interesting pattern to see is when the caregiver is experiencing repeated stressors (oscillating condition). In this case, caregiver CG1 shows monotonic increasing in his/her long-term stress. In contrary, caregiver CG2 experiences monotonic decreasing in his/her long-term stress. Similar condition also occurs in caregiver CG3 but decreases much faster and with lower oscillation compared to the condition in CG2.

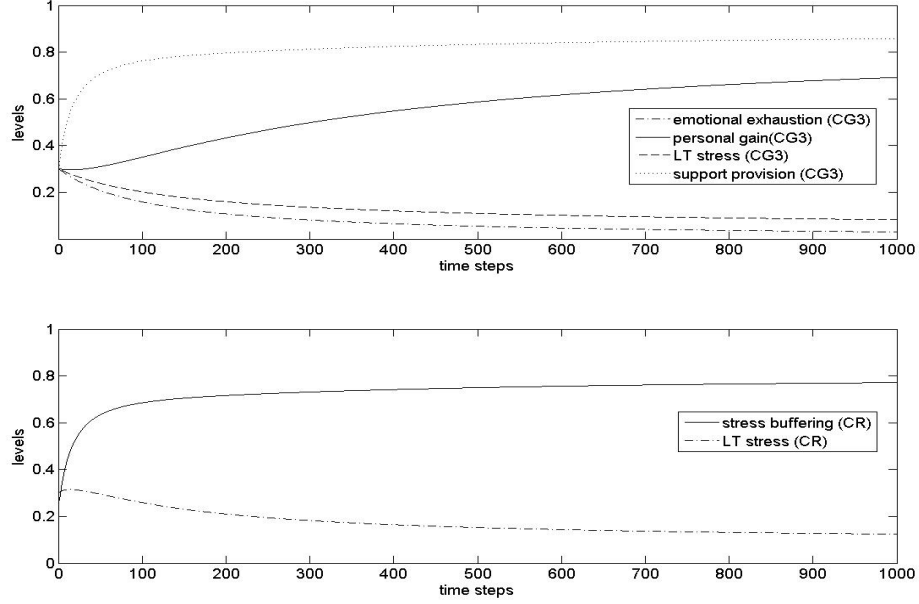


Fig. 9. An Effective Caregiver (CG3) without Support, and a Bad Care Recipient(CR).

6 Verification of the Simulation Results

In order to verify whether the model indeed generates results that adherence to psychological literatures, a set of properties have been identified from related literatures. These properties have been specified in a language called Temporal Trace Language (TTL). TTL is built on atoms referring to states of the world, time points, and traces. This relationship can be presented as $\text{holds}(\text{state}(\gamma, t), p)$ or $\text{state}(\gamma, t) \models p$, which means that state property p is true in the state of trace γ at time point t [5]. It is also comparable to the *Holds*-predicate in the Situation Calculus. Based on that concept, dynamic properties can be formulated using a hybrid sorted predicate logic approach, by using quantifiers over time and traces and first-order logical connectives such as \neg , \wedge , \vee , \Rightarrow , \forall , and \exists . A number of simulations including the ones described in Section 5 have been used as basis for the verification of the identified properties and were confirmed. Note that t_b and t_e are the initial and final time points of the simulation period.

VP1: Monotonic decrease of long-term stress

For all time points t_1 and t_2 between t_b and t_e in trace γ_1

if at t_1 the value of the caregiver's long-term stress is R_1 and at t_2 the value of the caregiver's long-term stress is R_2 and $t_1 < t_2$, then $R_1 \geq R_2$.

$$\begin{aligned} &\forall \gamma: \text{TRACE}, \forall R_1, R_2: \text{REAL}, t_1, t_2: \text{TIME} \\ &[\text{state}(\gamma, t_1) \mid = \text{long_term_stress}(\text{cg}, R_1) \ \& \\ &\quad \text{state}(\gamma, t_2) \mid = \text{long_term_stress}(\text{cg}, R_2) \ \& \\ &\quad t_b \leq t_1 \leq t_e \ \& \ t_b \leq t_2 \leq t_e \ \& \ t_1 < t_2 \Rightarrow R_1 \geq R_2] \end{aligned}$$

By checking property VP1, one can verify whether a caregiver's long term stress decreases monotonically over a certain time interval. For example, the caregiver's long-term stress turned out to decrease over the second half of the trace for caregivers that have received and accepted the provided support or for an effective caregiver.

VP2: Decrement of a caregiver's long-term stress below a certain level x

A time point t exists such that for all $t_1 > t$ the value of long-term stress is at most level x .

$$\begin{aligned} &\forall \gamma_1: \text{TRACE}, \exists t \forall R: \text{REAL} [t_b < t < t_e \ \& \\ &\quad \forall t_1: \text{TIME} > t [t \leq t_1 \leq t_e \ \& \ \text{state}(\gamma, t_1) \mid = \text{long_term_stress}(\text{cg}, R_1) \\ &\quad \Rightarrow R_1 \leq x] \end{aligned}$$

Property VP2 can be used to verify whether a variable eventually approaches some (given) value. In the experiments reported here, $x = 0.3$ was used as a borderline value for long-term stress to assume a caregiver is effective to provide social support. In many cases, after following the advices, the caregiver will reach this borderline value. A number of more specific other properties have been identified and verified, such as the following ones, which compare cases with a specific type of support and cases without. Note that formalisation of such comparison properties makes use of the possibility to explicitly refer to traces in the language TTL; this is not possible in the usual temporal logical languages.

VP3: Effect of problem coping skills on a caregiver's long-term stress

After a caregiver has followed the programme to improve problem focused coping skills for some time, the long-term stress level is more reduced than for a caregiver who does not.

$$\begin{aligned} &\forall \gamma_1, \gamma_2: \text{TRACE}, \forall R_1, R_2: \text{REAL}, t_1, t_2: \text{TIME} \\ &[\text{state}(\gamma_1, t_1) \mid = \text{support_problem_coping} \ \& \ \text{state}(\gamma_2, t_1) \mid = \text{not} \\ &\quad \text{support_problem_coping} \ \& \\ &\quad \text{state}(\gamma_1, t_2) \mid = \text{long_term_stress}(\text{cg}, R_1) \ \& \ \text{state}(\gamma_2, t_2) \mid = \\ &\quad \text{long_term_stress}(\text{cg}, R_2) \ \& \ t_1 < t_2 \Rightarrow R_1 < R_2] \end{aligned}$$

VP4: Effect of realistic expectation on emotional exhaustion

After a caregiver has followed the support programme to reduce unrealistic expectation, the long-term emotional exhaustion is more reduced than for a caregiver who does not.

$$\begin{aligned} &\forall \gamma_1, \gamma_2: \text{TRACE}, \forall R_1, R_2: \text{REAL}, t_1, t_2: \text{TIME} \\ &[\text{state}(\gamma_1, t_1) = \text{support_realistic_expectation} \ \& \\ &\quad \text{state}(\gamma_2, t_1) = \text{not support_realistic_expectation} \ \& \\ &\quad \text{state}(\gamma_1, t_2) = \text{long_term_emotional_exhaustion}(\text{cg}, R_1) \ \& \\ &\quad \text{state}(\gamma_2, t_2) = \text{long_term_emotional_exhaustion}(\text{cg}, R_2) \ \& \\ &\quad t_1 < t_2 \Rightarrow R_1 < R_2] \end{aligned}$$
VP5: Effectiveness of support on provided support to the care recipient

A caregiver who follows the suggested support by an agent will provide better support to the care recipient than a caregiver who does not.

$$\begin{aligned} &\forall \gamma_1, \gamma_2: \text{TRACE}, \forall R_1, R_2, d: \text{REAL}, t_1, t_2: \text{TIME} \\ &[[[\text{state}(\gamma_1, t_1) = \text{support_realistic_expectation} \ \& \ \text{state}(\gamma_1, t_1) = \\ &\quad \text{support_problem_coping} \ \& \\ &\quad \text{state}(\gamma_1, t_1) = \text{support_add_personal_resources}] \ \& \\ &\quad \text{state}(\gamma_2, t_1) = \text{not support_realistic_expectation} \ | \ \text{state}(\gamma_2, t_1) = \text{not} \\ &\quad \text{support_problem_coping} \ | \\ &\quad \text{state}(\gamma_2, t_1) = \text{not support_add_personal_resources}] \ \& \\ &\quad \text{state}(\gamma_1, t_2) = \text{long_term_stress}(\text{cg}, R_1) \ \& \\ &\quad \text{state}(\gamma_2, t_2) = \text{long_term_stress}(\text{cg}, R_2) \ \& \\ &\quad t_1 < t_2 \Rightarrow R_1 < R_2] \end{aligned}$$
7 Discussion

In this paper, an ambient agent model was proposed that supports caregivers for depressed persons and promote their well-being. Caring for a depressed person may entail a serious risk for the health of the caregiver. The designed ambient agent integrates a domain model of the functioning of the caregiver and the care recipient and their interaction, adopted from [3]. It exploits model-based reasoning to monitor and assess the caregiver's state using this computational model. Based on these assessments dedicated support actions are generated that are tuned to the circumstances, thereby taking into account guidelines adopted from [7].

Although some applications have been designed to support persons with a depression (e.g., [2]), automated support for caregivers has not been addressed, as far as the authors know. The model introduced here was evaluated by conducting a number of simulation experiments for different scenarios and types of

caregivers, and formal verification of the outcomes of these experiments. These outcomes show that using the advices provided by the ambient agent results in improvement in the situation in comparison to not using such advices; for verification of this type of comparison properties (which are not representable in the often used temporal languages; see also [5]) the language TTL and its software environment [5] has proved its usefulness.

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Part VI

Discussion and Future Work

Chapter 14

Discussion and Future Work

“It is more fun to arrive a conclusion than to justify it.”

(Malcom Forbes)

Discussion and Future Work

We conclude this thesis in this final part. We recall our three research questions and summarize the answers to each of them. In addition, based on our work, we provide practical guidelines for further evaluation of the presented models. Implications towards other domains are also covered in this chapter. Then we conclude with recommendations for future research and some remarks.

1 Grand Challenges of Building Intelligent Support for Depressed Persons: How Far We Have Come

In the preceding chapters, we have given an exploration of computational models and ambient agent models to support persons with unipolar depression and their social support networks. In this section, we discuss the contributions of this thesis to answer our research questions in Chapter 1.

1.1 Summary of Contributions

This thesis is mainly structured according to four parts (excluding Part I and Part VI that describe introduction and discussion respectively), which comprises in total of 12 chapters. In the first part of the thesis, we addressed computational aspects related to individuals with a risk of unipolar depression. First, in Chapter 2, modelling temporal dynamics based on several concepts in relapse and recurrence is addressed. Concepts in neuroticism, social support, coping, and assertiveness are among the central foci of this model. Next, in Chapter 3, a computational model to describe dynamics of cognitive vulnerability is presented. It covers important aspects of cognitive hopelessness and its relationship to the progression of depression. Chapter 4 describes temporal dynamics of coping strategies, in which important mechanisms to cope with incoming negative events are covered.

In the second part of the thesis, we investigated the integration between the previously developed computational models within an ambient agent. Chapter 5 presents an ambient agent model to support relapse prevention. We integrated support based on assessment results related to coping ability, social withdrawal, and multiple severe risk factors using the BDI (belief-desire-intention) concept. In Chapter 6, we designed an ambient agent model that exploits a specific therapy (Rational Emotive Behavioural Therapy) to reduce the risk related to cognitive vulnerability in depression. Chapter 7 combines both cognitive vulnerability and coping strategies into a combined model. In addition, we

analyzed and compared two different therapies pertinent to different conditions in this combined model.

The third part covers computational models for depressed persons and their social support networks. In Chapter 8, by adopting the concept of weak and strong tie, we developed a model to describe support tie preference during depression. Based on this model, we extended our work (in Chapter 9) to develop a model that explains mutual support in coping with stress. It involves a number of conditions to explain the interaction between support provision and receipt within social networks when facing negative events. Chapter 10 introduces a computational model to illustrate an informal caregiving interaction during stress, and how a depressed person influences a support provision process. Chapter 11 presents a computational model that simulates the spread of negative mood in a social network, but at the same time integrates elements from Gross' emotion regulation theory, as the individuals' efforts to avoid a negative mood.

In the fourth part, we addressed the design aspects of ambient agent models to support depressed individuals and their social support networks. In Chapter 12, we described a configuration approach for the combined support of social support members from available social support networks. This configuration approach utilized some extensions (support recipient and provider references) from computational models as describe in Chapter 8, and Chapter 9. Chapter 13 describes an ambient agent model that integrates a computational model from Chapter 10 to assess the caregiver's state in order to generate dedicated actions that are tuned to the circumstances.

1.2 Related Work

Tackling the challenge of addressing computational models for persons with depression is multi-disciplinary in nature. As a result, the work is related to the disciplines involved, i.e., neuroscience, psychology and support technologies. The central focus in this related work section is only on work related to the thesis as a whole. For related work applicable to the specific cases studied, the reader is referred to the related section of that specific chapter.

I. Neurobiological Models of Depression.

Researchers used neurobiological models to uncover the underlying mechanism of nervous systems behind the observed processes. For example, many neuro-chemicals and hormones have been linked to the development of depression (e.g., norepinephrine, thyroid hormones). Previous studies have implicated disturbances in the Limbic Hypothalamic-Pituitary-Adrenal Axis (LHPA) as one of the neurobiological changes most consistently associated with a unipolar

depression [17][39]. Post-mortem studies have also found evidence of chronic LHPA activation in suicide victims with a history of chronic depression [40][42]. Another study has shown that the dysfunctional limbic-cortical model is able to explain that depression is unlikely to be the result of a single brain region but as a multidimensional level disorder affecting discrete and functionally integrated pathway [22][41]. Moreover, Disner et al. [19] has introduced structural neurobiological underpinnings of Beck's cognitive model of depression. It outlines the neurobiological events that are associated in schema activation, biased attention, and rumination. Although it is interesting to model depression processes based on a neurobiological context, nevertheless this thesis has aimed at describing such processes at a higher level of abstraction.

II. Support Technologies for Persons with Depression.

The mental health support system today has effective medications and intervention models with which to work, and the professionals in the support system know how to meet the needs of the target group it is meant to serve [25]. Using interactive media technologies, including the Internet-based [1][14], phone-based [9][21][31], and voice-response telephone calls [24][31][53] provide feasible adjuncts to the traditional clinic-based therapy. These technologies can both increase the effectiveness of the therapy, extend to reach patients with barriers to face-to-face interactions and help clinicians guide their patients to manage their depression [13]. For example, a number of studies have shown that internet-based cognitive behaviour therapy is recognized as an effective treatment choice and appeared to be well appreciated for by depressed persons [1][44][50]. Related work from these aforementioned technologies has been taken as a source of motivation for the support models presented in this thesis. The work in this thesis (in part II and IV) can also contribute to a more formal analysis of the design to utilize ambient agent models as a core technology to help persons with depression.

1.3 Answers to Research Questions

In Chapter 1, our problem statement led us to formulate three main research questions. These research questions provide the point of departure for this thesis. In this section, we provide answers to our formulated research questions. First, we address our first research question:

(R1): “How can theories from psychology about relevant aspects of depression be represented using computational models”?

Answering our first research question, we focused to capture important essences (e.g., concepts) in related theories (available in informal representation), and to make it available for a computational modelling process [2]. This is largely addressed by the design of computational models covering the important features. However, this not an easy task since depression is a very complex and difficult concept to study for which different informal theories exist. These involve a number of inter-related and confounding factors that make it difficult to be simplified into a single model. To overcome this problem, we designed and analyzed different models to address different theories within the scope of depression. For example, in Chapter 2 we used the Cognitive Motivational Relational Theory to explain the dynamics of coping strategies when a person is facing negative events and how it will lead to progression of the long-term stress. Table 1 shows which specific domain aspects and theories of dynamics in depression are addressed in which chapter.

Table 1. Overview of the Domain Aspects / Theories Addressed in Different Chapters of the Thesis.

Domains / Theories Used	Chapters											
	2	3	4	5	6	7	8	9	10	11	12	13
Recurrence and relapse	X			X								
Cognitive vulnerability		X			X	X						
Coping strategies			X			X						
Social tie Preference							X	X			X	
Caregiving Interactions									X			X
Mood contagion										X		
Emotion regulation										X		

Using this perspective, we have demonstrated that the models are able to highlight important elements needed to assess individuals' conditions and their social environment pertinent to the underlying theories. To do this, first we identified the detailed relationships between explained concepts using underlying theories and literature that describes the domain. The rationale for this is to ensure that essential properties (such as states and dynamics) to design our models are captured. Then, these important essences were translated into formal representations. Most of these formal representations (in our case,

computational models) have been specified either in a form of a set of differential equations or in a hybrid temporal language representation (LEADSTO). These representations were chosen with their respect of effectiveness to represent temporal dynamics from the selected theories. From the developed formal representations, we conducted a variety of simulation experiments to generate simulation traces. Using these simulation traces, we evaluated our models, in order to verify whether they follow a number of essential characteristics and patterns described by particular theories in the literature. In addition, the models have been designed to have both short and long-term mechanisms to recognize progression in states and dynamics of depression. For example, a short-term mechanism (e.g., short-term stress) indicates instantaneous effects from the interaction with the internal or external environment. The short-term mechanism is the precursor towards the development of long-term mechanism (e.g., long-term stress). Therefore, any changes at this part can be used to scrutinize potential progression in a long-term mechanism.

The next research question focuses on the design of ambient agent models.

(R2): “How can ambient agent models to support depressed persons be designed using the developed computational models?”

To answer this question, we investigated the context of how ambient agent models can be designed to incorporate a domain model (e.g., the agent uses information from this domain model to provide actions related to the predicted state of the human and the environment). To address this, we used a generic framework for an integrative ambient agent model as a guideline for our ambient agents development according to [10], [29]. In addition, the ambient agents were designed to have a mechanism to respond only when it is needed. It is important to avoid unwanted interruption; otherwise, supported persons will find it infuriating and feel being manipulated, or worse. In our work, we monitored the progression of depression, and together with pre-defined factors or symptoms to ensure ambient agents will be able to intervene at the right time. For instance, in Chapter 2, there are three conditions were evaluated, namely coping ability, social withdrawal, and severe cases. In this example, an ambient agent will only intervene to provide support if any of these three conditions is satisfied. Moreover, in Chapter 12, support provision and receipt matching process will be executed if an ambient agent evaluates there is a need of help, pertinent to the states of the support recipient.

Finally, our last research question deals with the primary quest to evaluate the presented model, in order to ensure any support from our ambient agent models can help depressed persons and its social environment.

(R3): “How can we evaluate the appropriateness of the domain models and support models?”

To address our last question, we evaluated properties (both local and global) that should hold based on the evidences from literature. Evaluation is one of the essential tasks of a modelling process. It aims to determine whether a given formal representation describes specified observed phenomena accurately. As for the local properties, we evaluated whether these properties reflect the main aspects in the theory by analyzing interaction among defined concepts using causal relationships that have been found in empirically founded literature. For instance, a relationship between long term, chronic and daily events has been investigated to evaluate properties involving negative events. Often, over a longer period, a process specified by temporally local properties in computational models generates patterns that can be considered as emergent phenomena or temporally global properties. In this thesis, we evaluated different types of global properties, as put forward by empirically founded literature. These types of properties are:

- Achievement properties.
These properties express that; given some conditions (initial and/or intermediate) eventually a certain state is reached. For example, in Chapter 7, we were able to identify a condition where a person will recover from depression after following a specific therapy.
- Equilibrium properties.
These properties concern resulting in a stable, balanced, or unchanging state in the process. For example, in Chapter 2, we are able to identify a condition when a healthy individual encounters less intense events, then he or she will never develop a new relapse case.
- Representation properties.
These properties explain how internal states relate to external states in past and /or future. They can be categorized into two specific types, namely: 1) backward representation relations (relations to the precursor conditions) and 2) forward representation relations (relations to the future conditions). In this thesis, we only conducted evaluation for forward representation relations. For example, in Chapter 3, we are able to identify a condition where a person will be vulnerable to depression if he/she has negative perceptions in all situations and received negative support from his/her social support networks.
- Comparison properties.
These properties concern the comparison of certain state properties at different time points (e.g., monotonically increasing or decreasing), or comparison between different generated traces (e.g., with or without a specific therapy). For example, in Chapter 13, we identify the

monotonic decrease of the caregiver's long-term stress after have received the provided support.

In this thesis, the evaluation of our models was done by providing formal representations of a computational model of the system, and the correspondence between these computational models and their simulation traces, and actually observed conditions (obtained from the empirically founded literature) [15]. To do this, we highlighted three aspects to be present: (1) a formal specification of a model, (2) description of the environment that the model is supposed to operate in, and (3) properties that the model is intended to fulfil [35]. Given these requirements, we have evaluated our models using a mathematical and/or hybrid logical verification techniques to search for how input patterns that the environment or persons could generate follow (or violate) the properties. Section 1.3 explains the techniques we used to evaluate the models. Table 2 summarizes the evaluated types of properties in all chapters of this thesis.

Table 2. Overview of Evaluated Properties in the Different Chapters of this Thesis.

	Chapters											
Properties	2	3	4	5	6	7	8	9	10	11	12	13
Achievement				X	X	X			X		X	X
Equilibrium	X	X	X				X	X	X	X		
Representation		X		X		X						X
Comparison					X	X					X	X

In summary, Table 3 recapitulates the contributions of each chapter related to respective research questions.

Table 3. Related Chapters to Answer Our Research Questions.

Research Questions	Chapters
R1: “How can theories from psychology about relevant aspects of depression be represented using computational models?”	Chapter 1, Chapter 2, Chapter 3, Chapter 8, Chapter 9, Chapter 10, Chapter 11.
R2: “How can ambient agent models to support depressed persons be designed using the developed computational models?”	Chapter 5, Chapter 6, Chapter 7, Chapter 12, Chapter 13
R3: “How can we evaluate the appropriateness of the domain models and support models?”	All chapters

In the next section, we will explain the evaluation techniques we used in our models.

1.4 Evaluation Techniques

In this thesis, we have explored two evaluation techniques for our models. These techniques are mathematical verification, and logical verification. For the mathematical verification, we used equilibria analyses to describe situations in models where the values (continuous) approach a limit under certain conditions and stabilize [6]. It means, if the dynamics of a system is described by a differential equation, then equilibria can be estimated by setting a derivative (or all derivatives) to zero. One important note that an equilibria condition(s) is considered stable if the system always returns to it after small disturbances [33]. For example, using this autonomous equation,

$$dy/dx = f(y)$$

the equilibria or constant solutions of this differential equation are the roots of the equation

$$f(y) = 0$$

These equilibria conditions are interesting to be explored, as it is possible to explain them using the knowledge from the theory or problem that is modelled. As such, the existence of reasonable equilibria is also an indication for the correctness of the model. For example, (in Chapter 2), using equilibria analysis, we are able to identify a condition when a healthy person encounters less intense event, then he/she will never develop a new relapse case. Similarly, in Chapter we have identified the condition when a problem-focused individual will never develop long-term stress that typically caused by a prolonged dependency on emotion-focused coping during heighten stressful events.

For the logical verification, we have utilized the ability of the Temporal Trace Language (TTL) and its software environment as a specification language and verification tool. TTL allows us to verify both qualitative and quantitative of process under analysis and has the ability to reason about time [7]. The interval of such checks varied from one second to a couple of months, related to the complexity of the models. Using this technique, simulation models can verified whether they satisfy certain expected global properties. For instance, the TTL was used in Chapter 7 and Chapter 13 to evaluate the effectiveness of a particular therapy or support related to particular conditions identified in a person. The special software environment developed for TTL, features both a Property Editor for building and editing TTL properties, and a Checking Tool that enables formal verification of such properties against a set of (simulated or

empirical) traces [8]. This checking tool provides support for the automated analysis of simulated traces. The language has a higher expressive power than a number of other standard temporal languages such as Linear Temporal Logic (LTL), and Computational Tree Logic (CTL) [15][26].

2 Research Implications

There are some interesting points learned from this thesis that are applicable to several other domains. In this section, we address potential contributions of this thesis for applications in ambient intelligence, and psychology domains.

2.1 Ambient Intelligence for Therapeutical Applications

Recent developments in ambient intelligence technologies provide new possibilities to contribute to personal care, where the progression in wearable technologies has made it possible to be used in daily routines [38][47]. Coupled with knowledge about the human, these technologies can show more human-like understanding and contribute to personal care based on this understanding. In this thesis, we have introduced some models (both computational and ambient agent) to serve as a building block to design ambient intelligence applications that are able to perform a more in-depth analysis of the human's functioning during depression. This directed work can be envisaged through the development of intelligent software and hardware to support persons with depression (or any mental illness).

2.2 Human-like Agents for Simulation-based Training Environments

From the simulation results, our models reflect the condition of processing that occurs in humans and its social environment during depression. These models do represent a new kind of tool in the evaluation and testing of human conditions corresponded to that event. Such models can be integrated with embedded, interactive, and human-like agents to simulate patients and its social environment conditions during the pinnacle of depression. In the hands of psychologists, these agents could be very useful to precisely manipulate different aspects of human personality and social environment to understand detailed mechanism that governs unipolar depression. The models will provide predictions for phenomena (especially the boundary conditions) that rely upon complex interactions with the world that are difficult to experiment (e.g. experiments that costly or unethical to conduct on humans) [3][23][28]. Equipped with those extensions, this thesis could be useful as a first step to create a virtual human or robot (and virtual environment) that can be further

used as a pedagogical tool or as another mean of experiment [28][36]. For example, an implemented virtual agent or robotic model also has benefits over direct experimentation on human subjects [20]. Accurate testing of these models through controlled and repeatable experiments can be performed. Furthermore, experimental variations can be used to isolate and evaluate single factors (whether environmental or internal) independent of many of confounds that affect normal behavioral observations [52].

3 Grand Challenges of Building an Intelligent Support for Depressed Persons: Future Directions

In this thesis, we have only begun to explore the question of building computational representations for ambient agent models. We believe there are many fruitful research directions this thesis could be advanced in the future. In particular, we acknowledge four main directions for future research.

3.1 Socio-Technological Artefacts

The term “socio-technological artefacts” is a broad generalization for the several devices, social networks, and systems that we may want to communicate with or through the ambient agent models [16][18][31]. There are two main reasons for connecting an ambient agent to other devices (or systems). First, the ambient agent needs more information about the physiological and environment conditions. This information can be acquired from an array of wearable sensors. Important considerations to be made are, these sensors need to be wearable, ultra low-power consumption, and can work in noisy and robust environments 24 hours a day. These requirements are vital to support regular interaction between these sensors to collect seamless and continuous data from individuals and its environment [5]. Furthermore, these sensors can provide information directly rather than the ambient agent trying to read them as a human would [46].

Second, technology used as a media to interact with users (human-agent interface). For this specific purpose, a media that connects the ambient agent to users must be simple in order to ease the burden of interacting with technology [4][37]. An example might be during the monitoring process, the results from an analysis model of an individual’s conditions must be presented in a way that can be understood by any user (e.g. a simple visualization tool and graph). It is technically pointless to have sophisticated features yet difficult to comprehend [48][5][49]. In sum, the ideal version of this technology means it can provide support anytime and anywhere with lightweight, and powerful (yet simple) user interfaces.

3.2 Integration of the Different Models for Depressed Persons

Models are a fundamental building block of theory. Different models often explain different aspects, phenomena and conditions that exist in reality. In this thesis, a number of different computational models have been developed to address specific aspects of depression. These models can be integrated to explain a larger spectrum about the development of depression within individuals (e.g., coping, vulnerability) and social support networks, and even within societal levels. As a first step, the integration can be done in a sense of related endogenous components (e.g., stress levels), or related exogenous components (e.g., personality). Another possible way is that different functions can be considered different models or the same function can be performed at different levels of abstraction [43]. From this perspective, researchers will be able to view in-depth relationship for each sub-model on a different abstraction level. However, the integration must adhere with the existing concept or theory that capable to describe in what basis such an integrated model can serve to explain the reality. In addition, the integration process should cater for any potential issues concerning the complexity and robustness problems that possibly could occur because of the integration [11][27].

3.3 Empirical Validation and Personalization

The mathematical and automated analyses described in Section 1.4 have been successfully performed to guarantee *internal* validity, but this does not guarantee that those computational models are directly applicable to real persons, and in particular, which personality parameter values fit to which person. Therefore, as a next step, empirical validation of the models (with respect to its purpose) needs to be performed. To do this, we are planning to perform empirical validation for our models. First, we need to design and execute experiments that keep human subjects in loop. Next, we will tune the models against the traces of human behaviour from those experiments. During this step, we will require to perform parameter estimation analysis to find relationships between results from the human experiments and parameters involved. The challenge of parameter estimation is to find a combination of typically noisy and redundant features that accurately predicts the target output variable while avoiding over fitting. Techniques such as Gradient-based parameter estimation, Simulated annealing, and Genetic algorithm can be used to serve that purpose [34][51]. At the end, this will provide empirical validation of the models and realistic parameter settings for types of persons.

3.4 Ethical Considerations

Ambient agents, as any technology can be abused. Information stored within these agents (models) can be used as a significant source of manipulation and control over individuals [5][12]. Therefore, it is important to know what kind of information should be stored, and who will have a full access into that storage. Sensitive information should be kept in anonymous ways in order to avoid unwanted manipulation towards the users of the ambient agents. The design of a system that protects the privacy of a user's information once it has been given to ambient agents is a challenging research area. Another important consideration to be made is to avoid unrealistic expectations from the users [49]. For example, if users are eventually come to rely on our ambient agents as sources of grounding for their beliefs about their well-being, and without really taking part to seek medical practitioners, then they could face the indistinct danger that these ambient agents are not designed to solve [4]. Therefore, the users need to know what the ambient agents can do and cannot do, and what expectations the user should have about their respective roles during the monitoring periods. In addition, it is important to acknowledge that these ambient agents are not designed to replace any professional practitioners but to provide an additional media between the patients and practitioners traditional loops.

4 Concluding Remarks

This thesis explored computational models and ambient agent models, to support depressed persons. Given this, this thesis represents one of the first steps in the development of technologies for providing a forefront to engage social support and provide assistant to suggest related cognitive and /or behavioural therapy to depressed person who may not otherwise have the benefit of a social support networks. For the applications in which the primary objective is not social support, this thesis provides a partial road map to develop personal (assistive) agents that be aware of human functioning process. For psychology, this thesis provides alternative tools and paradigms for investigating depression, and possible relationships in social contexts. As the technology improves and access to this will be widespread, it will be interesting to see what is the future may hold for ambient agents to help persons with mental disorders. After almost four-year investigation in this subject matter, we are in a unique position to believe that these ambient agent technologies may become a reality sooner than we imagine.

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