Development of a Probabilistic Graphical Structure from a Model of Mental Health Clinical Expertise

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This thesis explores the process of developing a principled approach for translating a model of mental-health risk expertise into a probabilistic graphical structure. Probabilistic graphical structures can be a combination of graph and probability theory that provide numerous advantages when it comes to the representation of domains involving uncertainty, domains such as the mental health domain. In this thesis the advantages that probabilistic graphical structures offer in representing such domains is built on. The Galatean Risk Screening Tool (GRiST) is a psychological model for mental health risk assessment based on fuzzy sets. In this thesis the knowledge encapsulated in the psychological model was used to develop the structure of the probability graph by exploiting the semantics of the clinical expertise.

This thesis describes how a chain graph can be developed from the psychological model to provide a probabilistic evaluation of risk that complements the one generated by GRiST's clinical expertise by the decomposing of the GRiST knowledge structure in component parts, which were in turned mapped into equivalent probabilistic graphical structures such as Bayesian Belief Nets and Markov Random Fields to produce a composite chain graph that provides a probabilistic classification of risk expertise to complement the expert clinical judgements.

Key Words: mental health risk assessment; probability graphs; chain graphs; knowledge representation; psychological modelling.

Dedication

..........eyi t'Oluwa se

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Chapter One

1. Introduction

In this chapter the motivation behind the thesis and the main objective of the research are highlighted against the backdrop of past methods and our chosen approach.

1.1 Motivation

Risk assessment is a fundamental part of life, whether it be a mundane decision about the chance of rain or a much more vital one about the risk of a nuclear power station malfunctioning. In the mental-health domain, predicting whether someone is going to commit suicide or engage in an act of violence is extremely difficult, partly because the likelihoods are so low but also because of the lack of statistical data. The Galatean mental-health Risk and Social care assessment Tool (GRiST) was developed to address these problems by modelling how expert mental-health practitioners make risk assessments (GRiST, n.d.). However, its accumulating database of risk data has become a resource for more probabilistic approaches such as probability graphs, which are well-suited for capturing and reasoning with uncertainty where there is prior knowledge structuring (Lucas, 2004). In the past, mental health risk assessment was predominantly carried out using unstructured clinical approaches but it has since been realised that the best results can be obtained by using a combination of both structured clinical judgements and actuarial tools, such as one based on a probability graphical model (Department of Health, 2007). This thesis explores the development of a probabilistic graphical structure from a model of mental health clinical expertise to be used for assessing risk.

1.2 The Risk Assessment Domain

The need to assess and predict risk is a requirement that cuts across a wide range of disciplines, which include finance, public health, engineering, insurance and the environment. Because risk is characterised by uncertainty, developing appropriate tools for its prediction and assessment often proves difficult. Risk assessments have been and are carried out with a wide variety of methods. In the mental health risk assessment domain most risk assessment methods can be characterised under one of two categories. These are the expertise and the actuarial methods. The expertise method refers to structured clinical judgements that are given by the clinicians or experts in the domain based on their past experiences, training and accumulated knowledge acquired over time. Whilst using the actuarial method statistical techniques based on established relations are used to make predictions (Dawes et al, 1989). In this method the predictions are independent of the judgements or bias of the expert carrying out the assessments. However, on the other hand the clinical judgement method is dependent on the particular expert carrying out the assessment and as such can be seen to be subjective. Actuarial judgements have been proven to generally give more accurate results (Dawes et al, 1989). Reasons for the better precision of actuarial methods include the removal of individual bias and subjectivity in the process. Also actuarial methods allow us to derive from large amounts of data the relations that exist between the various variables in the domain. This is in contrast to the clinical judgement where the predictions tend to be based on the knowledge accumulated by the single expert carrying out the assessment.

1.3 Difficulties of Accurate Predictions

Regardless of whether actuarial or clinical methods are used obtaining accurate predictions can be a complex issue. It has been proven that more accurate predictions tend to be obtained when actuarial methods are used (Dawes et al, 1989; Grove, 2005; Monahan and Steadman, 1994). In the case of clinical judgements the level of accumulated knowledge, experience and training that the expert has received directly impacts on the accuracy of the predictions. In spite of this fact of greater accuracy being obtained generally using actuarial methods, it is not the case that in every situation this will always be the best option. For instance, in cases that are uncommon, a clinician who has had firsthand experience of working with such a case might give better predictions based on this past experience than actuarial methods. This is especially so if the actuarial methods model covers 99% of cases (the common cases) but not the uncommon 1%.

To cover such instances (i.e. both uncommon and common cases) the combination of both actuarial and clinical techniques will present a holistic, all encompassing technique that should produce the best results. The approach used in this research falls into this latter category i.e. one that combines the use of both actuarial and clinical methods via the use of probabilistic graphical models. Although the GRiST fuzzy model (discussed later in Chapter 2) is a model based on structured clinical judgement, it collects comprehensive and precisely defined data for all risks that are automatically stored in a database and thus available for probabilistic analyses. The approach in this thesis results in the connection of both types of risk assessments methods in the linking of the GRiST clinical judgements to actuarial analysis via the use of a probabilistic graphical model.

1.4 Current Mental Health Risk Assessment Tools

A variety of tools are currently in use for mental health risk assessments. Whilst some of these tools are paper based others are electronic (Department of Health, 2007). The various tools cover different areas of the mental health domain (e.g. suicide, harm to others, vulnerability and so on). Some of the commonly used tools include Risk Assessment Management and Audit Systems (RAMAS, n.d.). RAMAS (Risk Assessment Management and Audit Systems) is made up of a set of structured clinical judgement tools and these tools relate to various aspects of mental health including self harm, vulnerability and harm to others (Department of Health, 2007). More information on RAMAS and its underlying scientific background and model can be found in O'Rourke et al (2001). Another tool is the Functional Analysis of Care Environments (FACE) which has both paper and electronic formats (FACE, n.d.). FACE is a mental health risk assessment tool that integrates clinical and management information (Elzinga and Meredith, 2001) and comprises of assessment tools that cover such areas as substance abuse, forensic services and mental capacity (Department of Health, 2007). More on FACE and its underlying assessment features and methodologies can be seen in Elzinga and Meredith (2001).These and some other tools are summarised in (Department of Health, 2007).

1.5 Highlights on the Use of Probabilistic Graphical Models in Decision Support Systems based on Expert Knowledge

Over the years there have been different types of decision support systems (expert systems). The initial types of expert systems did not incorporate the modelling of uncertainty but were more logic oriented. Examples of this can be seen in the rule based system where you have rules of the form, *if some assertions holds THEN some assertion is true/perform some action* (Cowell et al, 1999). Mycin, which was developed for the diagnosis and treatment of meningitis and infections of the blood, is an early example of a rule based expert system (Shortliffe and Buchanan, 1975). Other types of expert systems include those based on classification trees which, like the name suggests, are used to predict an object's membership of a class (Cowell et al, 1999). The various logic based decision support systems have their advantages but also have limitations (more on these can be seen in Cowell et al, 1999). However, the limitation of interest to us relates to the incorporation of uncertainty in these models. It was not until later that attempts were made to include uncertainty in these models. For the rule based systems the initial attempts consisted of an extension of the systems to include certainty factors. For instance in the

1970s Shortliffe and Buchanan implemented the certainty factor model for Mycin (Heckerman,1992).

The use of probabilistic graphical models as we know them today became prevalent after the pioneering work of Judea Pearl on Bayesian networks and probabilistic graphical models in the mid eighties. The initial probabilistic graphical models that tended to be used in decision support systems were directed graphs (also known as Bayesian belief networks) and an extension of these known as influence diagrams. Another type of graphical model which have gained wide use especially in the imaging and machine learning domain is the undirected graphical model (also known as Markov random fields). The properties and usage of these probabilistic graphical models in decision support systems for risk assessments will be discussed in greater depth in Chapter 3.

The ultimate aim of this research is the development of a principled approach for translating the mental health risk expertise contained in GRiST into a probabilistic model which will serve as an alternative risk assessment method based on probabilistic knowledge. GRiST is a psychological model for mental health risk assessments based on fuzzy sets (Buckingham, 2002). For the initial stages of the research the focus was on the conversion of the GRiST knowledge structure into Bayesian Belief Networks. This was primarily because of the suitability of Bayesian Belief Networks and their associated methods for capturing and reasoning with uncertainty (Lucas, 2004).

However a major challenge soon ensued, namely the identification of causal relationships between the various GRiST nodes and in particular how to retrieve or interpret causal information within the GRiST fuzzy model. This was a major issue because in the Bayesian belief networks the direction of the edges between nodes needs to be from cause to effect. The initial proposed solution was to be based on the assumption that the knowledge elicitation task given to the experts resulted in a causal knowledge structure but upon careful examination and analysis of the nodes in the model, the conclusion was reached that this was not necessarily the case in all situations. So the issue of how to extract causal relations from GRiST for modelling in the Bayesian Belief Network still remained. This then led to an exploration of two possible solutions:

- The first option was to consider other methods which do not require causality (e.g. models needing no causal relations defined) to model the probabilistic risk assessment model. The specific structure investigated here was the Markov

Random Field, which is an undirected graph without causal connections. Again this will be discussed further in Chapter 3.

- The second option explored was to stick to the original plan and use Bayesian belief networks but come up with a means of extracting the required causal relations between the variables in the GRiST knowledge structure. For the semantics contained in the GRiST knowledge structure, the identification of causal relations for this option will have been important because the model contains inherent causal knowledge. This causal knowledge can be seen in a general way as the definition of the risk factors that contribute to the occurrence or likelihood of occurrence of the top risk (e.g. suicide or harm to other).

However neither option was satisfactory in itself because it is clear that the GRiST knowledge structure comprises of a mixture of both causal and non-causal associative relations. For this reason, a third option was explored: a graphical structure that will provide a means of accurately modelling both the causal and non-casual relations inherent within the GRiST knowledge structure. Chain graphs are suitable candidates and are considered in the next section.

1.6 The GRiST Approach

The GRiST approach is via the use of chain graphs. Chain graphs are graphical models which allow both directed and undirected graphs with the constraint that they do not have semi directed cycles (Lauritzen and Wermuth, 1989). Within a chain graph variables which are linked with a directed edge have a causal relationship between them and, in a similar fashion to Bayesian belief networks, the direction of the edge is from cause to effect. On the other hand an undirected edge between two variables represents an associative relationship between the variables, which is how edges are represented in Markov random fields. Hence chain graphs are seen to be a generalisation of both Bayesian belief networks and Markov random fields and are thus able to model both causal and non-causal relations within a single model. Once it was ascertained that the GRiST knowledge structure could indeed be modelled by a chain graph and that this was the best path to follow, the rest of the research then focused on the translation of the GRiST knowledge structure into a probabilistic chain graph to be used for mental health risk assessments. We discuss both the generic chain graph and the development of the GRiST chain graph in detail in subsequent chapters. A method is then also devised to translate the formal specification of expert knowledge within the GRiST hierarchical structure into appropriate graphs and, eventually, the integrated chain graph. Figure 1.1 depicts the various stages leading to the final GRiST chain graph, from initial elicitation of expertise to final chain graphs that can be used to predict risks (the PhD research starts at the third block with the analysis of fuzzy GRiST knowledge structure to build component structures).

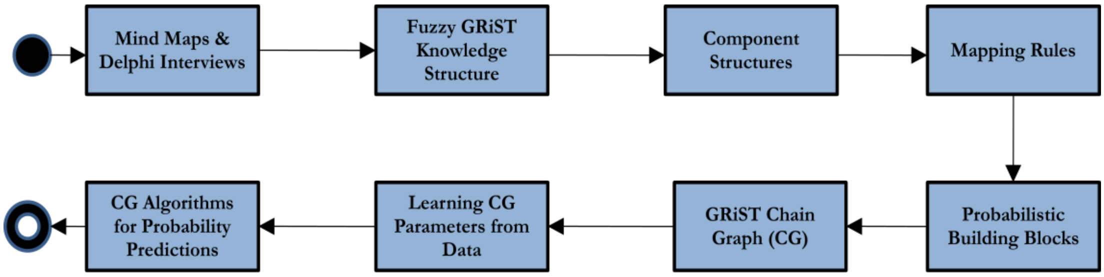


Figure 1.1: GRiST chain graph development stages.

1.7 Contributions

This thesis contributes to the translation of knowledge-based systems using hierarchical expertise into probabilistic graphical models. For the translation, a new approach based on a set of mapping rules is presented. The mapping from the fuzzy model to a probabilistic graphical model is defined and implemented for the GRiST knowledge structure. The methods discussed in this thesis could be applicable to other systems based on hierarchical expertise, especially ones that contain both causal and non-causal relations. The possibility of representing both causal and associative relations in the same model helps to model domains more accurately, which has a direct impact on the quality of the results of the risk assessments performed using the tool. Forcing domains to fit into either a directed or non-directed graph can result in a loss of accuracy between the domain being modelled and the final resultant model. The GRiST chain graph circumvents this limitation and the research will show how it improves accuracy of the risk predictions.

1.8 Thesis Outline

In this section the remaining chapters of the research are summarised. In Chapter 2, the GRiST knowledge structure is presented in detail, including its representation and its uncertainty propagation. This is followed in Chapter 3 by a discussion on the various types of probabilistic graphical models used in this research and their use in risk assessments and decision support systems. Chapter 4 explores the relations contained within the

GRiST knowledge structure and the semantics and different visualisations of the GRiST knowledge structure. In Chapter 5 the mapping rules for translating from the GRiST knowledge structure right up to the GRiST chain graph are defined. In Chapter 6, the application of the GRiST chain graph to GRiST data: the specific model, its implementation, and how the data is processed are discussed, this is followed by the testing and evaluation of the developed model in Chapter 7. Discussions and conclusions are then presented in the final chapter (Chapter 8).

Chapter Two

2. GRiST Knowledge Structure

In this chapter we discuss the GRiST knowledge structure and its uncertainty representation and propagation. The mapping of the GRiST knowledge structure into probability graphical models is also introduced.

2.1 GRiST Knowledge Structure Representation

The Galatean Risk Screening Tool (GRiST) is a decision support system for mental health risk assessments that represents knowledge in a hierarchical tree structure for generating risk evaluations (Buckingham, 2002). It is a psychological model for mental health risk assessment based on fuzzy sets and the knowledge structure encapsulates the semantics of the clinical expertise. In this section we explore the various aspects of the GRiST knowledge structure.

2.2 GRiST Fuzzy Model

The GRiST knowledge structure (i.e. the fuzzy model), was directly derived from the expertise of mental health domain experts. It is hierarchical in form, which is in line with other knowledge representations derived from expertise (Rossiter, 2002). The GRiST knowledge structure was specifically developed from encapsulated knowledge from 46 domain experts and was subsequently validated and refined with the involvement of over 100 multidisciplinary clinicians (Buckingham et al, 2007; Buckingham et al, 2008). The GRiST tree is an XML (eXtensible Markup Language) structure made up of a set of nodes, which can either be concept or datum nodes. XML is a markup language that describes the structure of data (in this case the GRiST knowledge structure) and provides a flexible and powerful way to describe knowledge structures, more on XML can be seen in Dix et al (2001). A datum node is a component value representing a physically measurable item of information or cue influencing risk evaluations (e.g. the seriousness of intention to commit suicide “seriousness” as shown in Figure 2.1).

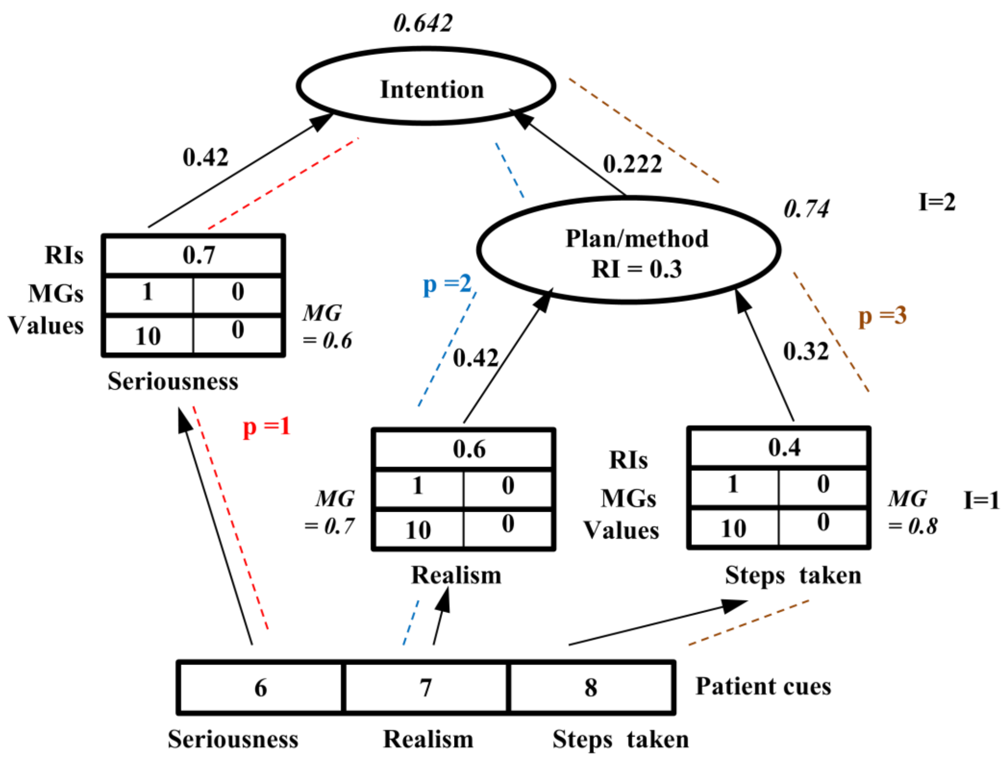


Figure 2.1: Example of the propagation of membership grades in the GRiST model, highlighting the path to levels, p, for the concept node *intention*.

Datum nodes equate to the information gathered during an assessment and are the input values to the tree (i.e. the leaf nodes). Appendix 2 contains a full version of the GRiST questionnaire used to collect the values that map to the datum nodes. Concept nodes are the higher-level nodes in the tree consisting of two or more subcomponents that could be datum nodes or other concept nodes. They represent composite concepts underlying risk such as depression. Next we describe how uncertainty is represented and propagated in the model, the definition of its data structures and directly following on from these, the component structures that it decomposes into.

Uncertainty in the GRiST fuzzy model is represented using two main measures; relative influences and fuzzy-set membership grades:

Relative Influence (RI) represents the influence or weight a node has on its parent concept, relative to its siblings. Within the GRiST knowledge structure there is a constraint stating that the total sum of RIs across the siblings must equal one.

Membership Grade (MG) represents the degree of membership of an object in a node, where each node is considered to be a fuzzy set i.e. an MG represents the degree of membership of an object in a node of the tree, with each nodes's MG ultimately contributing to the top-level risk membership (e.g. suicide and self-harm).

In the GRiST knowledge structure, datum or leaf nodes match associated patient cues, which generate an MG from an MG distribution that has been defined by clinical experts as part of the elicitation process for the decision support system. These MGs feed through the concept hierarchy based on the RI values attached to nodes as illustrated by Figure 2.1 and equation (2.1) (see Buckingham (2002) for further details).

$$MG(X) = \sum_{p=1}^{p} MG(datum_p) x \prod_{l=1}^{l} RI_{lp}). \qquad (2.1)$$

Equation (2.1) states that that the membership grade of a concept, *X*, such as 'intention' in Figure 2.1, is equal to the sum of the MGs of the datum nodes along all paths *p* to *X* multiplied by all the corresponding RI values along the paths on each level *l* leading to *X.*

The following example of how the MG at a concept is calculated uses equation 2.1 and Figure 2.1. Applying equation 2.1 to Figure 2.1 above with the total number of paths $P = 3$ and levels $L = 2$:

At path *P* = 1, we get the membership grade of *seriousness* multiplied by the RIs along the path *P* = 1 (i.e. 0.7) i.e. 0.6 x 0.7.

Likewise when path *P* = 2, the membership grade of *realism* multiplied by the *RIs* along path *P* = 2 (i.e. 0.6 and 0.3) i.e. 0.7 x 0.6 x 0.3.

Similarly for path *P* = 3, the membership grade of *steps taken* multiplied by the *RIs* along path *P* = 3 (i.e. 0.4 and 0.3) i.e. 0.8 x 0.4 x 0.3.

Summing all these together then gives us the membership grade μ at the *Intention* concept as

$$\mu(Intention) = (0.6 \times 0.7) + (0.7 \times 0.6 \times 0.3) + (0.8 \times 0.4 \times 0.3) = 0.642.$$

The general topology of a fuzzy model is made up of three main components, the encoder, the processing module and the decoder (Pedrycz and Gomide, 1998). These components directly map to the inference process of traditional models. The inference process starts with the inputs into the model, and then moves on to the fuzzifier stage, which in turn leads to the inference engine and finally the last stage in the process is the defuzzifier stage. Below is an illustration of how GRiST inference relates to these stages using the example from Figure 2.1 above.

Inputs: *seriousness = 6, realism = 7, steps taken = 8*

Fuzzify Inputs (convert from crisp input which are exact or distinct inputs using membership distributions of datum nodes), the membership grade values μ of the following are: $\mu(seriousness) = 0.6, \mu(realism) = 0.7, \mu(stepstaken) = 0.8$

Inference Engine: Propagation of membership grades up the tree using equation (2.1) to yield μ(Intention) = 0.642

Defuzzify: Final membership grade of top risk, in this example μ(Intention) = 0.642, would with actual top risks (e.g. suicide risk) be mapped to a linguistic variable, such as *low, medium* or *high* risk.

In traditional fuzzy models, some of the operations used in the processing module (i.e. the inference engine) are:

- the *min* operator to represent *AND*, this is used because it maintains results of the *AND* truth table and extends to real numbers as well
- the *max* operator to represent *OR* (for same reason as the *min* operator)
- the *1-**X*** to represent *NOT **X***

Furthermore, in these modules every rule contributes to the final solution. The same is true with the GRiST model where an increase in the membership grade in any node results in an increase in the root risk. The above briefly relates GRiST to traditional fuzzy models, for more on fuzzy models refer to Pedrycz and Gomide (1998).

2.3 The GRiST Fuzzy Uncertainty Representation and Probability Theory

The parameters needed for risk prediction in the final probabilistic graphical model will be learned from data. However, it is still important to explore the bridging of the gap between the GRiST fuzzy uncertainty relationship and probability theory. This is because the relationship between the membership grades and conditional probabilities in GRiST can both aid the parameter learning process and be used in the validation of the final probabilistic graphical model. The next section therefore discusses the various issues pertaining to bridging the gap.

There are ongoing disputes between different proponents of fuzzy set theory and the more traditional probability theory. However, the one element that holds true regardless of which side of the fence one sits on is that both theories aim to model uncertainty. This PhD research takes the position that based on the particular model and the uncertainty representation, one or the other or at times even using a hybrid of both would be the most appropriate route to take. Membership grades are not a probabilistic measure. However, they have a relationship to probabilities and it is this relationship that will be discussed in the remaining part of this section.

2.3.1 GRiST Membership Grades and Probability

Fuzzy set theory and probability set theory differ both mathematically and semantically. The main mathematical difference between the two is that probability theory obeys the law of the excluded middle (i.e. an object is either a member of a set or not). Whereas the law is not valid for fuzzy sets where expressions of the type *Tomatoes are both fruit and not fruit* are supported. In addition, for probability distributions the sum of the probabilities of a variable over all possible values of the variable is 1 (see equation 2.2), however equation 2.3 is not necessarily the case for membership functions (Dubois and Prade, 1993).

$$\Sigma_{u \in U}\, p(u) = 1. \tag{2.2}$$

$$\Sigma_{u \in U}\, \mu(u) = 1. \tag{2.3}$$

The above reaffirms the semantic difference between fuzzy and probability set theory: probability theory deals with crisp well defined sets and an element is either fully a member of the set or not; in fuzzy set theory, the set is ill defined and elements can have degrees of memberships in the set. For example, consider the following statements

There is an 85% chance that patient X is depressed.

The above statement supposes that patient X is either depressed or not, and one has an 85% chance of knowing whether or not he is.

Patient X's membership grade within the set of depressed people is 0.85.

The above supposes that patient X's membership of the set of depressed people is 0.85.

In other words in probability theory there is an 85% chance of the patient being depressed or a 15% chance of the patient not being depressed. The point, however is that a patient is either depressed or not depressed which is in contrast to the fuzzy theory statement which implies that a patient can be partially depressed (in the above example 85% so).

The bridge being explored between the GRiST uncertainty representation, probability theory and eventually the probabilistic graphical model starts from the underlying conditional probability definitions ingrained in the GRiST semantics. Therefore the areas that are explored and utilised in this thesis include the relationships between the membership grade distributions of the leaf nodes as given by the experts and their possible / potential relationship to likelihoods, probabilities and joint probability distributions. The importance of any discoveries in relation to the conditional probabilities and joint probabilities, become more apparent when we consider the link between conditional independences and a probability graph's joint probability distributions later on in this thesis.

2.4 Considerations in Relating Membership Grades and Probabilities

In Figure 2.2 a sample membership grade distribution for a datum node is depicted. The x-axis shows values that can be entered for the particular datum node whilst the y-axis shows associated membership grade values. These mappings were set by the experts positioning required points in the graph, thereby giving the membership distribution for the datum node. This was done for each of the datum nodes in the model. In defining the values of the MGs the experts were not assigning probabilities. Instead they were estimating relative probabilities with values relative to the maximum probability the variable can have. As the real probability is not known, the experts assigned a MG of 1 to represent the maximum membership or influence that the variable can have. For further details on how the experts carried out this task see Buckingham and Adams (2007).

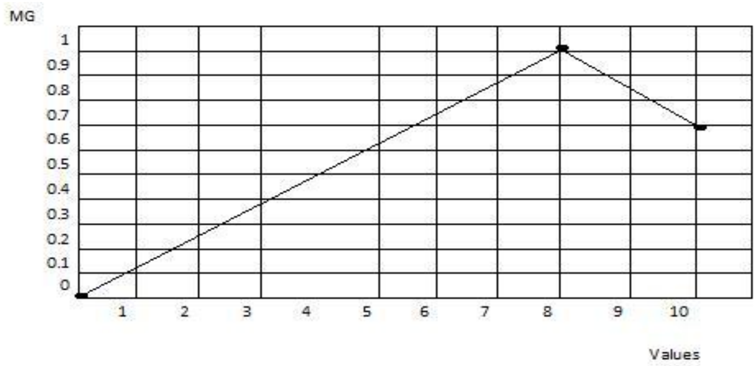


Figure 2.2: Membership grade distribution of datum node.

From an examination of the semantics of MGs in the GRiST model, there are some areas in which it is possible to infer the relationship between MGs and probability.

The areas relating to the fuzzy to probability relations that were explored include the fact that for most concept nodes, the MG measures the degree to which a person maximises the associated risk with respect to the particular concept, without knowing the exact extent of its contribution to that risk. The actual contribution to the risk is given by the degree to which the MG is filtered out on the way up to the risk node (i.e. given by the RIs along the path). The question is: considering the MG of the datum, how can it be translated into a probability of the risk, given the concept nodes MGs along the path and the filtering RIs? For example given the past attempts concept, the MG in this concept is a measure of how close the patient is to a person who would have maximum risk with respect to the concept in question. If the $\mu(Datum)$ = 1 the implication is that $P(MaxRisk|\,\mu(Datum))$ = 1, where *MaxRisk* refers to the Maximum Risk that the particular node can contribute independently of any other.

However we do not know what the *MaxRisk* value is but as the RIs given by the clinicians measure the relative contributions to risk of the underlying concepts, it is possible to approximate to it from them. Considering the relationship between the RIs of sibling nodes, we see that on each level in the GRiST model, the contribution from a node to the *MaxRisk* value is equal to the general *MaxRisk* value on that level multiplied by the RI value of the said node.

$$MaxRisk = MaxRisk_1 \times RI_1 + MaxRisk_2 \times RI_2 + \ldots + MaxRisk_n \times RI_n . \qquad (2.4)$$

In relating current findings to previous work done on the bridging of the fuzzy to probability gap, the above is similar to results obtained when Bayesian methods are used as a link between the fuzzy representation and probability theory. As mentioned by Ross et al (2002), Bayesian methods can be used as a link between fuzzy and probability theory. Bayes rule states that the probability of a hypothesis *h* given evidence *e* is equal to the product of the probability of evidence *e* given the hypothesis *h* and the prior probability of the hypothesis divided by the probability of the evidence *e* (Pearl, 1997). The rule is depicted in symbols in the equation below:

$$P(h \mid e) = \frac{P(e \mid h)P(h)}{P(e)}.$$

Using Bayesian methods as a link between the fuzzy representation and probability theory involves interpreting the MG as a likelihood function i.e. $\mu_R(Datum)$ is the likelihood function of *Datum* for a fixed set *R* (where *R* stands for *Risk* and refers to the highest node in the category). The idea is then to obtain a probability based posterior *P(Risk|Datum)* from a probability based prior *P(Datum)* and the likelihood function (i.e. the MG). The above assertion is true because the definition of a MG is subjective and as mentioned earlier, it gives the expert's opinion on the degree of membership in a category, where a category refers to the top risks which are the highest level concepts. The full GRiST fuzzy knowledge structure consists of four main categories; *suicide*, *harm to others*, *self harm* and *vulnerability* but this research only considers *suicide*. In addition to this, likelihood functions are not necessarily probabilities and so in this particular case, the likelihood function is not taken to be a probability value but rather a positive MG value.

Attempting to translate the GRiST knowledge structure into a probabilistic equivalent requires understanding GRiST's uncertainty processing in conjunction with the semantics of its knowledge structures and any constraints operating on them. The data structures can be further broken down into the following types as defined in the GRiST fuzzy model's knowledge structure; further information on this structuring and with their corresponding constraints can be found in Buckingham and Adams (2007).

1. Non-Generic Concept – These are concept nodes occurring just once in the model.

2. Generic Concept – These are concept nodes that occur in more than one location but always with an identical structure. They may be one of two subtypes:

- Context Independent Generic Concepts, generic concepts (g) which have exactly the same uncertainty values (RIs) wherever the concept node occurs;

- Context Dependent Generic Concepts, which are known as generic distinct (gd) nodes because their uncertainty values (RIs) are dependent on the location of the nodes in the hierarchical tree.

3. The same definitions for components that apply to concept nodes (defined in points 1 and 2 above) also apply to datum nodes.

Figure 2.3 below, summarises the different GRiST concept node types:

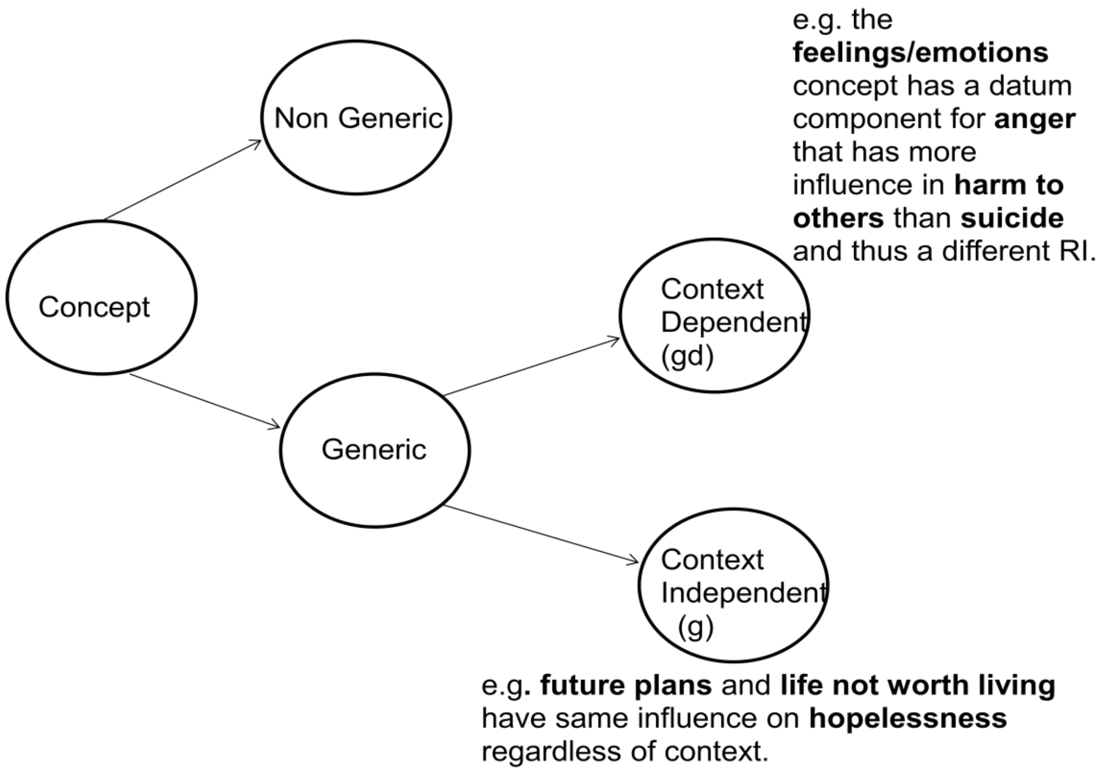


Figure 2.3: Summary of GRiST concept node types (gd – generic distinct and g – generic).

The naming conversions for the two different types of generic components (i.e. generic distinct and generic) are the original names in the GRiST fuzzy model. However for additional clarity, in this thesis generic components will be referred to from now on as fixed generic (FG) components and generic distinct components will retain the same name i.e. generic distinct components (GD).

2.5 GRiST Component Structures

Following on from the semantics of the GRiST fuzzy model's data structures and its uncertainty propagation, a list of constraints has been generated. The general knowledge structure was decomposed into three possible component structures (fixed generic component structures - FG, generic distinct component structures - GD and the non generic component structures). The objective behind decomposing the GRiST knowledge structure into a group of smaller component structures is the identification of structures that are likely to be useful for creating probabilistic graphical models. To add clarity some special terms are defined in relation to the GRiST knowledge structure and its decomposition into component structures. Figure 2.4 will be used where necessary to illustrate the definitions further.

- A root node of a component structure refers to the highest ancestor node in the structure under consideration. For example from Figure 2.4 if the subsection of the GRiST knowledge structure is split into various sub graphs (i.e. component structures) including the component structure made up of *gen-phys-hlth-prb* (physical health problems), *gen-phys-hlth-deg-diag* (when life-threatening or degenerative illness first diagnosed), *gen-phys-hlth-pain* (pain), *gen-phys-hlth-disa* (disability), *gen-com-imp* (communication impairment) and *gen-phys-hlth-det* (deterioration in physical health). Then the root node of this structure is *gen-phys-hlth-prb*. Please note that a full listing of the GRiST knowledge structure node names and their full labels is given in Appendix 1.

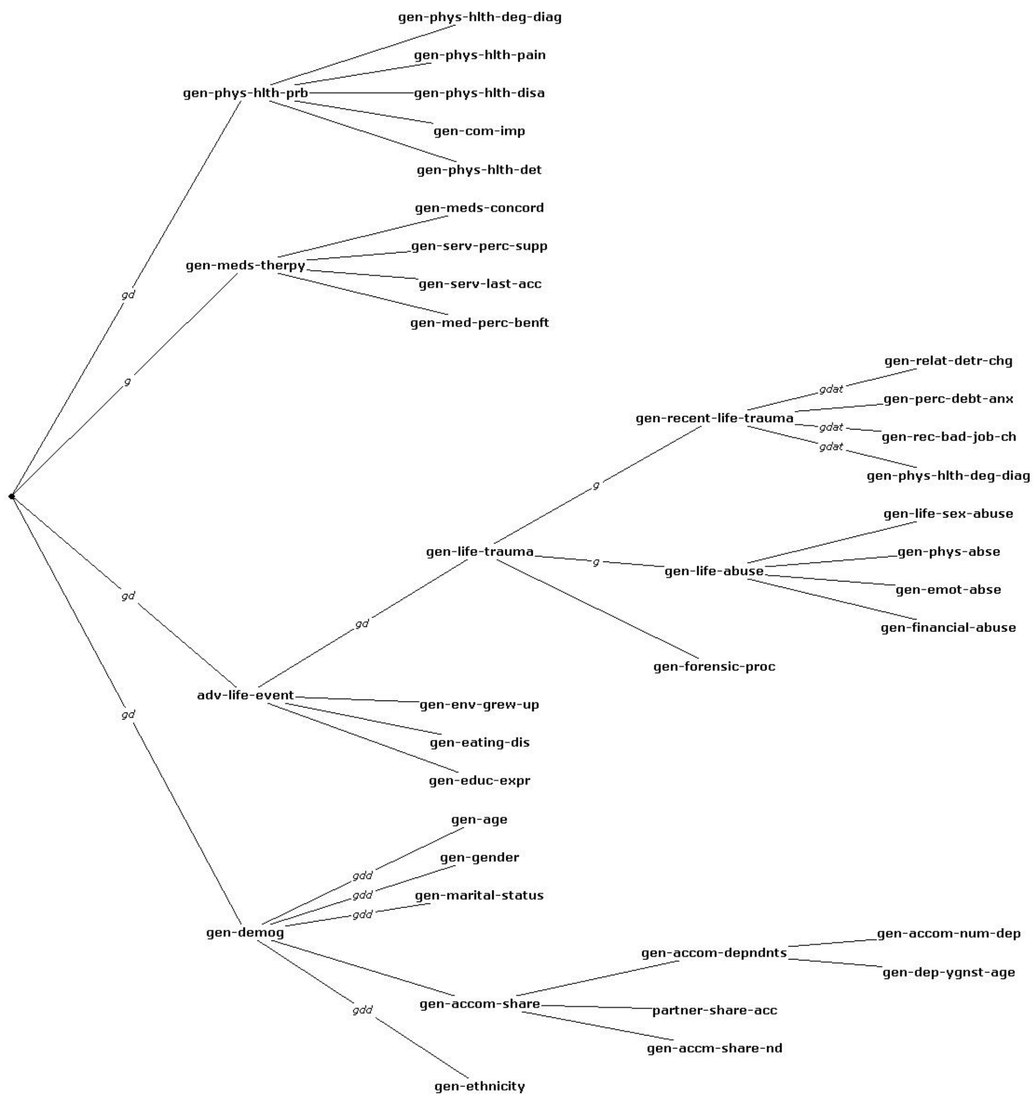


Figure 2.4: Subsection of the GRiST knowledge structure, depicting different FG and GD component structures (*'g' and 'gd'* denote 'FG' and 'GD' components respectively; whilst *'gdat'* and '*gdd*' are the datum node equivalents).

- The internal nodes of a component structure are the descendent nodes of the root node of the given structure. So for instance in the example previously consider in Figure 2.4, the internal nodes of the component structure are *gen-phys-hlth-deg-diag* (when life-threatening or degenerative illness first diagnosed), *gen-phys-hlth-pain* (pain), *gen-phys-hlth-disa* (disability), *gen-com-imp* (communication impairment) and *gen-phys-hlth-det* (deterioration in physical health). These are all the nodes of the structure except the root node *gen-phys-hlth-prb* (physical health problems).

- The type of a component structure is dependent on the type of its root node (i.e. fixed generic, generic distinct or non generic). So for instance in the component structure with root node *gen-phys-hlth-prb* of Figure 2.4, as the root node is of the type *gd* (i.e. generic distinct) the component structure is of the type generic distinct. In a similar vein the component structure with root node *gen-meds-therpy* is of the type fixed generic because its root node is of the type fixed generic.

To summarise, a GRiST component structure is made up of a root node and internal nodes and its type is dependent on the type of the component structure's root node. Another useful definition is that of the top risk, a top risk is different from a root node, in that the top risk refers to the highest node for the entire GRiST knowledge structure and not just a single component structure. As mentioned in section 2.4 the full GRiST fuzzy model comprises of four top risks (*suicide*, *harm to others*, *self harm* and *vulnerability*) but the focus in this research is on *suicide.*

2.5.1 Fixed Generic Component Structures (FG)

A GRiST component structure which has a root node of the type fixed generic is known as a fixed generic component structure. An example of this can be seen in Figure 2.4 for the component structure with root node *gen-meds-therpy*. For the root node of a FG component structure its MG value is the same regardless of its location in the overall knowledge structure. This in turn means that the relevant context of the FG component structure is its root node. Within (and only within) the root concept the uncertainty values of the internal nodes are fixed and always remain the same regardless of location.

- The MG of the fixed generic component structure type is always the same throughout the entire knowledge structure and hence the root concept node is the context that its MG relates to.

- the internal nodes of FG component structure remain fixed in relation to the root concept i.e. the context of the internal nodes here is its root concept node.

This implies that the uncertainty values of the FG component structure are not based on the top risk (as this changes across various parts of the GRiST knowledge structure, whilst the FG's MG remains constant) but is in fact based on the root concept node hence explaining why the MG value of the FG structure can and does remain fixed even when the top risk changes. It should be noted that the change in top risk refers to change in values and not change in the top risk's structure.

2.5.2 Generic Distinct Component Structures (GD)

For GD component structures, the case is a bit more complex and it can be further split into two different types:

- Those whose root concept do not have any generic node ancestors (e.g. *gen-ser-ment-ill* – serious mental illness in Figure 2.5); these are the pure GD component structures with both varying internal RIs and varying root concept MG. The context for these nodes is the top risk of the model in which it occurs. This type of structure has been named the generic distinct with no fixed generic ancestor component structure (GD).

- GD component structures with fixed generic node ancestors along their path; the context for these structures is determined by the fixed generic ancestor. The closest fixed generic ancestor node to the top risk (along the hierarchy) will define the behaviour of both the root concept and the internal nodes of the GD structure. In relation to the closest fixed generic ancestor node all the nodes of the GD structure will have fixed RIs and behave like FG structures. This is very different from the behaviour that would have been observed for the same structure had it not had a fixed generic ancestor (in this case the internal nodes will have varying RIs). An example from Figure 2.5 is *gen-feel-emot* (i.e.feelings and emotions) which is of the type generic distinct but has a fixed generic ancestor in *gen-depression* (i.e. depression). This type of structure is also a generic distinct but with a fixed generic ancestor (GD with fixed generic ancestor).

2.6 GRiST Component Structures Constraints

To aid in the conversion to the ultimate GRiST probabilistic model, the GRiST knowledge structure was analysed and the constraints that defined the possible subcomponent structures that it can be decomposed into were identified. In the next subsection these constraints are summarised in text and Figure 2.6.

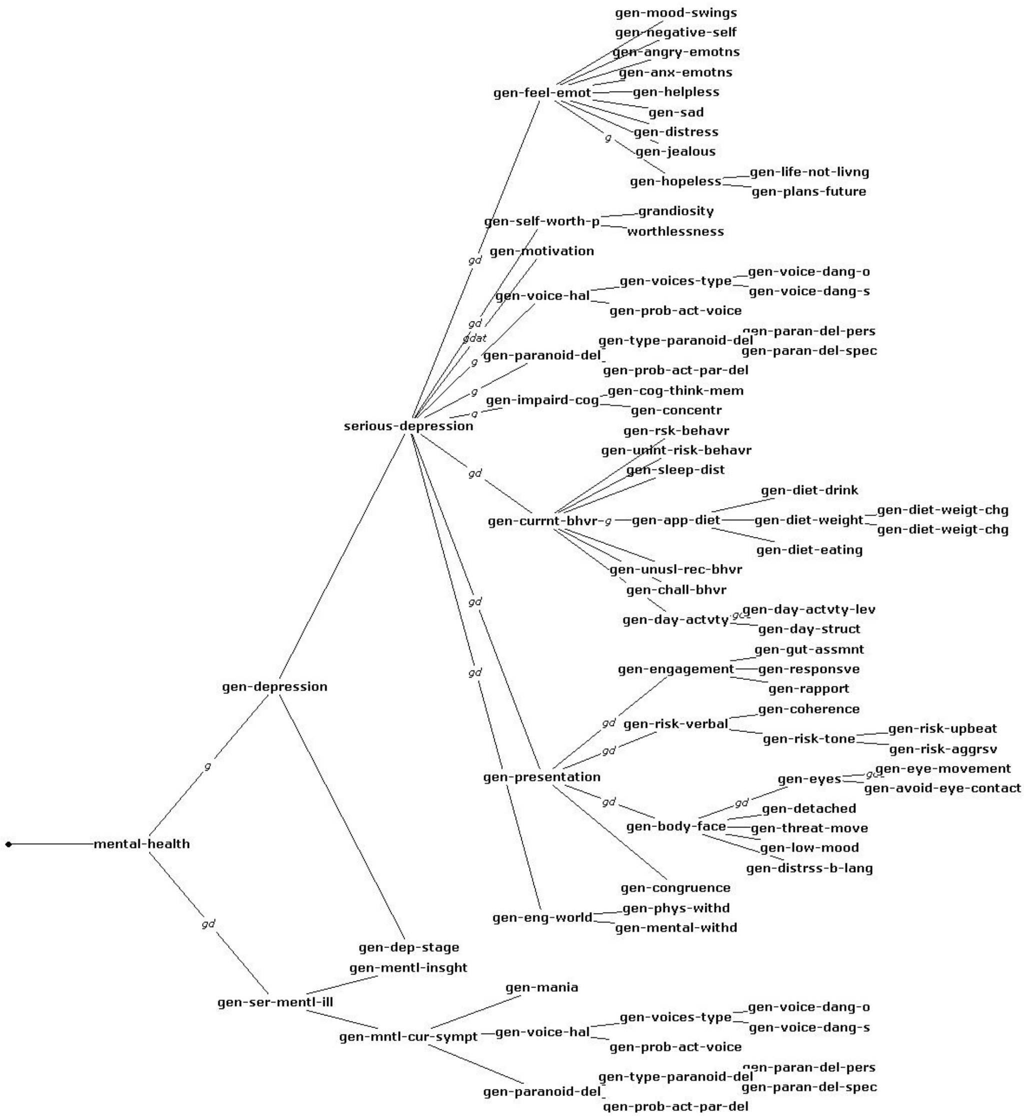


Figure 2.5: Subsection of GRiST suicide knowledge structure – depicting depression and other structures (‘*g’ and ‘gd’* denote ‘FG’ and ‘GD’ components respectively).

The identification of these constraints is important because from them the conditional independencies encapsulated by the GRiST knowledge structure can be discovered. Then in the mapping to the probabilistic graphical model, the main objective will be to translate the GRiST knowledge structure into a probabilistic graphical model that accurately represents the conditional independence relations present in the GRiST knowledge structure.

2.7 Constraints Related to Structures with Generic Distinct Root Nodes

The following are the constraints that fall under this category:

- The RI value of the root node varies. This is the case because the root node's RI is in the context of sibling nodes, where its sibling nodes are other nodes (X_1 to X_n) that link to the same node Y as the root node in the direction of the top risk. If the root nodes location changes so will the sibling nodes. However, if the component structure has a fixed generic node ancestor, in this case character traits exhibited by the component structure will be determined by the ancestor node.
- The MG value of the root node varies.
- The RI values of the internal nodes vary.
- If a generic distinct node has at least one node of fixed generic type as an ancestor then the context (or point of reference) for the generic distinct node is the nearest ancestor to the top risk of the type fixed generic. Otherwise, the context for the generic distinct node is the top root risk node (e.g. suicide, harm to others and so on).
- In the case where all the internal nodes of a generic distinct root concept are of the type fixed generic, if all the MGs and RIs of these internal nodes are always fixed it is obvious that the root concept MG value cannot vary and will itself always be fixed too, which is incorrect behaviour for a generic distinct root concept. This therefore leads to the constraint that a root concept of the type generic distinct cannot have all its internal nodes to be of the type fixed generic. To make it possible for the variation in the root concept's MG value in various locations, there must be at least one internal node of the type generic distinct. This is seen to be true in the GRiST knowledge structure and is a good test of the validity for generic distinct node definitions.

2.8 Constraints Related to Fixed Generic Component Structures

The constraints that fall under this component structure are as follows:

- The RI value of the root node varies.
- The MG value of the root node is fixed.
- The RI values of the internal nodes are fixed.

- Given that the MGs and RIs of all internal nodes are fixed then the point of reference (i.e. the context) for the internal nodes is their root node. An alternate way of viewing this constraint is that there are no changes in the uncertainty values of the fixed generic node between different locations because the context remains unchanged (i.e. root node remains fixed). An example from the GRiST knowledge structure is *depression* and its internal nodes (see Figure 2.5).

- As every node within a root concept of the type fixed generic has a fixed RI and MG everywhere the root concept occurs, if one of the internal structures is of the type generic distinct, it will also need to have fixed RI and MG values within the context of the root concept everywhere it occurs. This is not the default or usual behaviour of generic distinct nodes, but is in fact a special case.

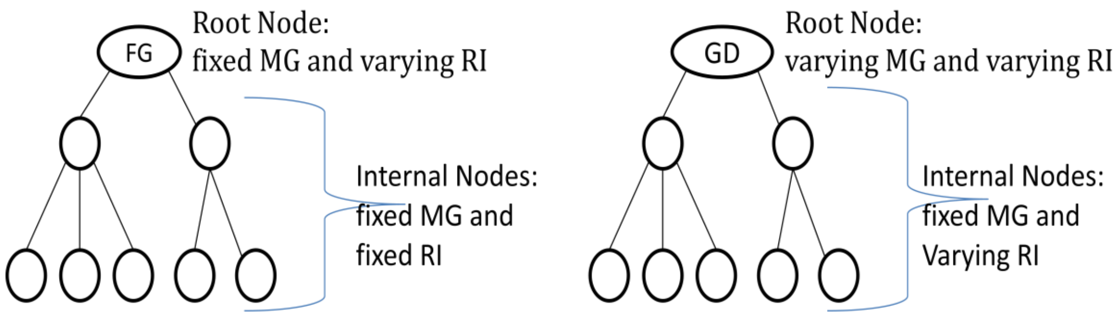


Figure 2.6: Uncertainty properties of fixed generic (FG) and generic distinct (GD) component structures.

Further discussion on these component types and the analysis that leads to these categorisations are given in section 4.7.6 page 97.

2.9 The Probabilistic Graphical Models

Having described the component structures that the GRiST knowledge structure can decompose into, the next stage involves the identification of conditionally independent relations between various variables in the GRiST knowledge structure. This will enable the GRiST knowledge structure to be divided into categories of equivalent graphical structures and each one can be translated into an associated probabilistic structure. The task then becomes one of constructing a single probability graph out of the smaller probability building blocks but an important issue to address is ensuring that conditional independence represented in the GRiST knowledge structure is maintained during the translation process, as indicated in Jiang et al (2005) and Kim (n.d.). However, unlike in these instances, the variables in the components that we are aggregating do not overlap (i.e. we are not combining the overlapping data from different models). This distinction makes it easier for the integrity of the conditional independence relationships to be maintained during the conversion process.

There are two main types of graphical models, those based on undirected graphs, which are known as Markov Random Fields and model symmetric relationships between their variables, and those based on directed graphs known as Bayesian Belief Networks that model causal relationships between their variables. A Bayesian Belief Network is a directed acyclic graph (DAG) consisting of nodes (that represent random variables in the domain being modelled) and directed arcs between the nodes, which represent direct dependencies. A Markov random field on the other hand is an undirected graph which, unlike Bayesian belief networks, does not encode causal relations. However in the Markov random field the probability distribution of each variable is dependent only on its graphical neighbours (local Markov property for Markov random field). Examples of these two graphical models can be seen in Figure 2.7.

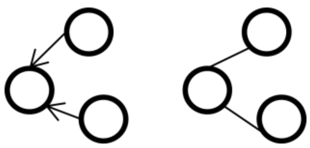


Figure 2.7: Simple Bayesian Belief Network (directed graph) and Markov Random Field (undirected graph).

The probability models are discussed in more detail in Chapters 3 and 5. The important thing to note now is that the probability building block that a GRiST component structure maps to is dependent on the conditional independences (and dependencies) represented in it and the nature of the relations it encapsulates. For example are the relations causal or non causal? In Chapter 4 an in-depth analysis is done of the GRiST knowledge structure. This analysis covers aspects such as the component structures it decomposes into, and the possible relations between its nodes and their properties. Chapter 4 also contains a detailed examination of different visualisations of the GRiST knowledge structure, the objective underlying all this being to correctly map each component structure to the probability building block that can most accurately represent it, and this culminates in the mapping rules for the conversion from the GRiST knowledge structure into appropriate probability building blocks in Chapter 5.

2.10 Mapping the Component Structures into Probability Building Blocks

The preceding sections on the GRiST component structures and their ingrained constraints lay the foundation for the exploration of the semantics encapsulated in the GRiST knowledge structure, this will be discussed in detail in Chapters 4 and 5. From these semantics the conditional independence relations represented by the GRiST knowledge structure will then be identified and mapped into probability building blocks. These building blocks represent different types of probabilistic graphical models which the GRiST component structures can be adequately mapped to. From the GRiST knowledge structure constraints and the component structures that it can be decomposed into that were discussed earlier in this chapter, the potential for the need to have different modelling approaches for the mapping to probability graphical models has started to surface. In Chapter 4, this is delved into in more detail, including other areas such as the inherent semantics in the knowledge structure, the relationships it contains and so on. This results in the need to model some aspects of the knowledge structure in a causal fashion and some in a non causal way. The two types of probability graphs (i.e. the probability building blocks) that make this possible are directed graphs (also known as Bayesian belief networks) and undirected graphs (Markov random fields). This will all be discussed in more detail in subsequent chapters.

This chapter has introduced the basic knowledge structures representing mental-health expertise and their inherent constraints. In Chapter 3 the probability building blocks and their properties will be explored, whilst Chapter 4 examines the component structures and their constraints in more detail, with a view to defining the semantics more precisely, and attempts to produce a formal ontology. The aim is to produce a specification of the structural and uncertainty relationships with the GRiST expertise that enables a principled transformation of that expertise into an equivalent probabilistic knowledge structure. The mapping rules from GRiST into the probability building blocks will then be discussed in Chapter 5. This will be followed by the construction of the GRiST chain graph for the mental health risk assessments from the probability building blocks. Chapter 6 will cover the construction of the chain graphs. This will include the learning of parameters from data and its conversion to factor graphs for inference purposes. Finally Chapter 7 will cover the testing and evaluation of the constructed chain graph for mental health risk assessments.

Finally summarising the overall process of mapping from the GRiST knowledge structure to the final GRiST probabilistic graphical model (i.e. chain graph) for mental health risk assessments, the steps are:

- Identification of the different knowledge component structures within the GRiST hierarchy (this process has been started in the current chapter).
- Conversion from the GRiST component structures to probability building blocks (Chapters 4 and 5).
- Construction of the GRiST chain graph from the probability building blocks (Chapters 5 and 6).
- Learning of parameters from the chain graph (Chapters 6 and 7).
- Conversion to factor graph (Chapters 6 and 7).
- Application of the factor graph for probability predictions (Chapter 7).

Chapter Three

3. Probabilistic Graphical Models

In this chapter we discuss various probabilistic graphical models and their use in decision support systems for risk assessments.

In this chapter, the probabilistic graphical models to be used in the conversion process from the GRiST knowledge structure are discussed. The chapter starts with a general overview of probabilistic graphical models and then goes on to describe and compare the graphical models that are potential building blocks. This is then followed by a discussion of the more complex probabilistic graphical models that are produced from the probability building blocks.

Probabilistic graphical models are an amalgamation of probability and graph theory and can be used to represent a wide variety of domains. They make it possible to represent the knowledge structures of domains in a graphical format whilst at the same time maintaining probabilistic properties for the structures represented. There are different probabilistic graphical models and each has its own set of constraints and properties. However, a common property that they all share is that they represent the joint probability distribution of the variables that they encapsulate. Probabilistic graphical models can also generally be factorised into local conditional probability distributions (of their variables), which in some form make up the joint probability distribution of the graph. The graphs generally fall into one of two categories; directed and undirected graphs, there is however also a third category which subsumes both the directed and undirected graph and these are the sets of graphs that are a combination of both directed and undirected graphs. In this thesis, the probabilistic graphical models of interest are the undirected graph Markov random field, the directed Bayesian Belief Network, the undirected factor graphs and the mixed chain graphs (Figure 3.1).

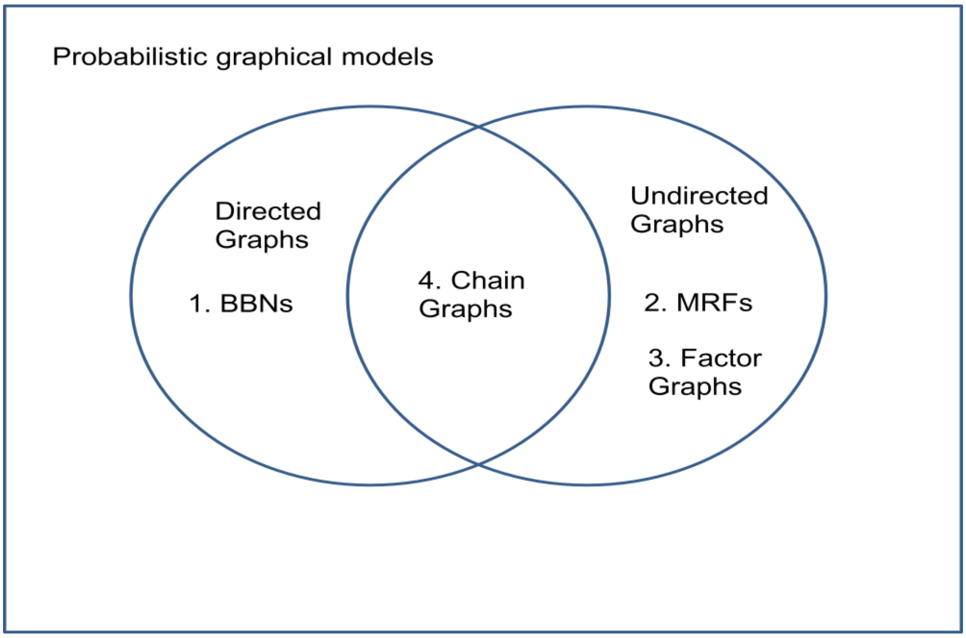


Figure 3.1: The probabilistic graphical structures used in this research (adapted from Murphy, 2003).

3.1 General Graph Definitions

In a graphical structure variables within the domain to be modelled are represented as nodes and dependencies between the nodes are represented as edges. Where there are no edges connecting nodes together this represents conditional independencies.

A graph can be defined formally as:

$G = (V, E)$ where G represents the graph, V the set of nodes and E the set of edges that exist between nodes.

For the different types of graphical structure there are a set of properties which are known as Markov properties, these define the conditional independencies that the structures contain. Figure 3.2 depicts a simple graphical structure and will be used to define terms commonly used in the domain.

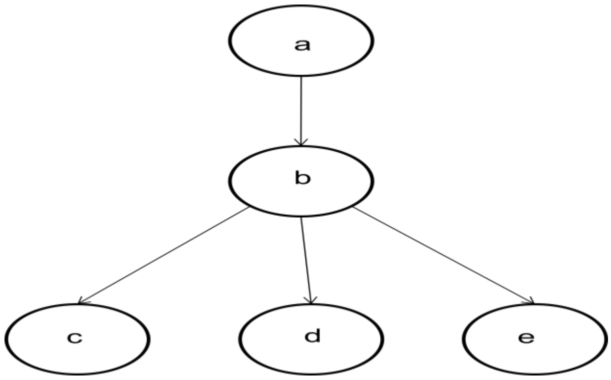


Figure 3:2: Simple directed graph.

Below are the definitions necessary for this work:

- Link – A link refers to connection between two nodes, where a link exists this implies that some sort of relationship exists between the nodes (this will be explored further in subsequent sections). For example in Figure 3.2 there is a link between **a** and **b**.

- Causality – this encapsulates the notion of node **a** causing node **b** (see Figure 3.2). The direction of causality (i.e. cause to effect) is the same as the directed edge. That is the node with the arrow head going into it is the effect whilst the source node is the cause. In Chapter 4, further details on causality are discussed.

- Dependence – Any two nodes in a graphical structure are connected to an edge if they are dependent in some way on each other. The dependency can be of different forms (e.g. causal or symmetric and so on). In Figure 3.2 nodes **c, d** and **e** are dependent on node **b**, as is node **b** on node **a**.

- Conditional independence – The absence of an edge between nodes indicates that they are conditionally independent of one another. The conditions vary for the different types of graphical models. This will be discussed in more detail later in the chapter when each type of graphical model is considered. An example of the notation to be used is as follows $c \coprod a \mid b$ implies **c** is conditionally independent of **a** given **b**.

- In graphical models, nodes are sometimes described as being observed or unobserved. Observed nodes are variables whose values are physically measurable whilst unobserved nodes values are not. For instance the frequency of past suicide attempts by a person is physically measurable whereas a person's current risk of suicide is not.

- Parent Nodes – Some of the terms used in graph theory have been borrowed from family trees and this is one of them. The notion of parent nodes is only applicable in directed graphs, and a node is parent to another node if it is higher up the hierarchy and directly linked to the other node. Examples from Figure 3.2 include **a** to **b** and **b** to nodes **c**, **d** and **e**.

- Siblings – Sibling nodes are nodes that share a common parent, so from Figure 3.2, nodes **c**, **d** and **e** are sibling nodes.

- Child Nodes – Children nodes are the reverse of parent nodes, they are directly linked to the node higher up the hierarchy.

- Path – A path refers to a set of connections between any two nodes in the structure, where unbroken links do not exist between the nodes i.e. between the two nodes there exists a sequence of nodes such that there is a link between the all the nodes that fall between the original nodes (for whom the path is being defined). For example there is a path between **a** and **d** (via **b**).

- Ancestors – This is only applicable for directed graphs and refers to all nodes with paths to a node **x** that are higher up in the hierarchy than **x**. Node **a** is an ancestor to nodes **b**, **c**, **d** and **e** in Figure 3.2.

- Descendants – Again this is only applicable for directed graphs and refers to all nodes with paths to a node **x** that are lower down in the hierarchy than **x**. Nodes **b**, **c**, **d** and **e** are descendants to node **a** in Figure 3.2, it is the opposite of ancestors.

- Neighbours – of a node are all the other nodes linked to it via an undirected edge.

- Boundaries – The boundaries of a node *X* in a graph are either the neighbours of *X* (undirected graphs) or the parents of *X* (directed graphs).

The most important question that a graphical model must answer here via its structure is what are the conditional independence relations represented in the model i.e. what are the Markov properties represented by the graph (Koller and Friedman, 2009). In the subsequent sections of this chapter the probabilistic graphical models to be used in the research have the conditional independencies that they can represent discussed.

3.2 Bayesian Belief Networks

Bayesian networks, with their associated methods are suited for the development of risk assessment models as they are well-suited for capturing and reasoning with uncertainty (Lucas, 2004), especially so in various industry sectors where it has, and is increasingly proving to be an extremely useful tool for risk assessments. Examples of some specific areas in which Bayesian Belief Network models have been used for risk assessments include:

- Breast Cancer Risk Prediction (Ogunyemi et al, 2004; Euhus 2001)
- Haemodialysis (Rose et al, 2005)
- Risk Analysis in Investment Appraisal (Savvides, 1994)
- Software Metrics (Xu et al, 2006)
- Operational Risk (Alexander, 2003; King, 2001; Verrall et al, 2007)

The term ‘Bayesian Network’ was coined by Judea Pearl to express a formalism that is a combination of probability calculus and graph theory (Pearl, 1985). The actual origins of Bayesian belief networks however traces back to Bayes theorem, which is discussed later in section 3.2.1 on page 45.

Bayesian Belief Networks are directed graphical representation of probabilistic relationships, where the graphical representation consists of nodes (representing the relevant variables in the model) and edges between the nodes. These edges represent informational or causal relationships between the variables. The strength of influence of one node on another node within a Bayesian Belief Network is captured by the probability distribution of nodes. For example, if within a Bayesian Belief Network model, one node *depression* is linked to another node *suicide attempt*, the probability distribution of the *suicide attempt* node would be an indicator of the strength of influence that the node *depression* has on it. Bayesian Belief Networks thus allow observations to be made about known variables and the inferring of the probabilities of others (Fenton and Neil, 2004).

Risk assessments have traditionally been undertaken in a variety of ways, some of which are documented in previous reviews (e.g. Bennett and Jacik, 2005). This section focuses solely on the use of Bayesian Belief Network modelling for risk assessments. It begins by taking a critical look at Bayesian Belief Networks and their potential for risk assessments, with a view to identifying past and current use of Bayesian Belief Networks in risk assessments, their manner of usage and advantages and disadvantages encountered in implementation. This is done by starting with a general review of Bayesian Belief Networks and considerations of risk assessments; this is followed by a concluding section before then continuing with the discussions on the other types of probabilistic graphical models to be considered.

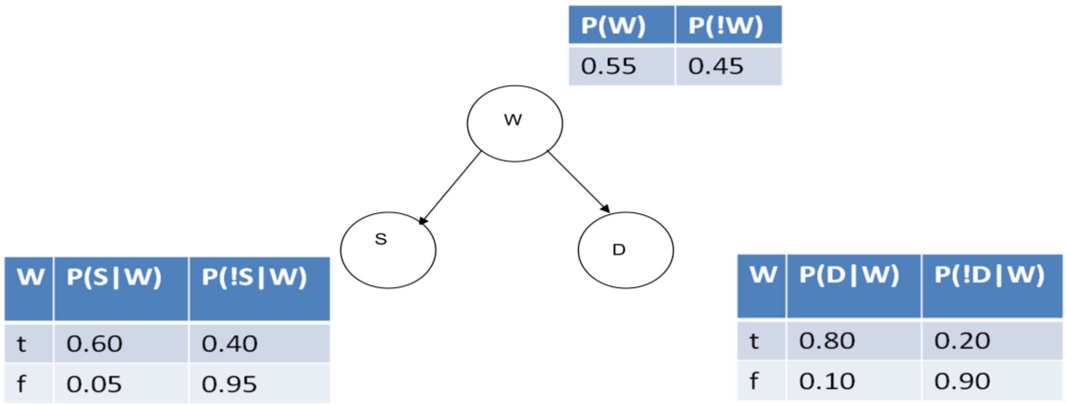
3.2.1 Fundamentals of Bayesian Belief Networks

According to Korb and Nicholson (2003:29) “a Bayesian Belief Network is a graphical structure that allows us to represent and reason about an uncertain domain”. In this context, an ‘uncertain domain’ is whatever area the risk assessment model is required in such as mental health suicide risk.

In addition, within a Bayesian Belief Network, for discrete domains, each node has a conditional probability table (CPT) which quantifies the relationships between the nodes. This is done as follows: for each node, all possible combinations of its parents are specified and the probabilities of the child taking the value of each of these combinations are then specified in a table (the CPT).

Figure 3.3 depicts a diagram illustrating a simple hypothetical Bayesian Belief Network. The arcs between the nodes show the causal dependencies between the nodes, and the CPT shows strength of influence of the nodes on each other as follows (these values are purely for illustrative purposes).

The prior probabilities of *Deep sense of worthlessness* (W) are given as 0.55 being the probability that W will be true and 0.45 the probability that it will be false. Note that these two probabilities sum up to make a total of one, this is because the total probability across all the possible states that a variable can take is one (i.e. P(S|W) + P(!S|W) = 1, given that S can only hold two possible states T or F). The notation ‘!S’ used in the preceding sentence means ‘not S’. Focusing on the next node *sleeplessness* (S), its conditional probability table illustrates that the probability of **S** being true given that its parent node **W** is known to be true is 0.60, likewise given that the **W** is known to be true the probability of **S** being false is 0.40. The *depression* **D** conditional probability table can also be interpreted in a similar manner. More will be said later on the relationship between a node’s parents and its conditional probability distribution.



P(W)	P(!W)
0.55	0.45

W	P(S|W)	P(!S|W)
t	0.60	0.40
f	0.05	0.95

W	P(D|W)	P(!D|W)
t	0.80	0.20
f	0.10	0.90

W = Deep sense of **W**orthlessness **S** = **S**leeplessness **D** = **D**epression

Figure 3.3: Hypothetical graph depicting simple Bayesian network.

A Bayesian Belief Network represents the joint probability distribution of all the variables in it and this joint probability distribution can factorized into a product of the variable's local conditional independent distributions.

For example the joint probability distribution of all the variables in Figure 3.3 can be represented as follows:

$$P(W,S,D) = P(W)P(S\,|\,W)P(D\,|\,W).$$

Bayesian belief networks are based on Bayes rule (Pearl, 1997)

$$P(h\,|\,e) = \frac{P(e\,|\,h)P(h)}{P(e)}.$$

This asserts that the probability of some hypothesis *h*, given evidence e is equal to the *likelihood* of the evidence given the hypothesis has occurred, $P(e\,|\,h)$, multiplied by the probability of the hypothesis prior to any evidence being given, $P(h)$ normalized by $P(e)$ (Korb and Nicholson, 2003). This gives a mathematical rule based on probabilities that outline how to change existing beliefs in light of new evidence (Murphy, n.d.), where the *P(h|e)* is the posterior probability of the hypothesis after it has been adjusted with the new evidence from its prior probability, *P(h),* when the evidence was not known.

As noted earlier, a Bayesian Belief Network is a graph consisting of nodes that represent variables in the world to be modeled (this for example could be suicide risk and its associated risk factors), and directed arcs between the nodes. These directed arcs represent direct dependencies between the variables and are always one-headed arrows linking two nodes together. Any two nodes so linked are assumed to have a causal dependency between them and in a similar vein, absence of a linking arc between any two nodes implies causal independency (Anderson et al, 2002).

The only constraint to specifying the arcs in Bayesian Belief Networks is that directed cycles are not allowed i.e. a node cannot be its own ancestor or descendant. For illustrative purposes, if two nodes A_i and A_k have a causal dependency where A_i causes A_k (i.e. A_i is the parent node of child node A_k), this is represented as follows; $A_i \to A_k$. A situation whereby $A_i \to A_k \to A_n \ldots \to A_i$ is not allowed. A Bayesian Belief Network can therefore be defined as a Graph *G* of the following form:

$G = (V, E)$; if $(x, y) \in E$ then $(y, x) \notin E$.

With only directed edges and no directed cycles (i.e. no directed path from x to x

$\forall x \in V)$.

In the next section the representation of conditional dependencies for the Bayesian Belief Network is discussed in detail. Their implications for the GRiST structure will be covered in Chapter 5.

3.2.2 Bayesian Networks and their Markov Properties

Bayesian belief networks use a directed acyclic graph to represent a set of random variables and their conditional independencies. The independencies represented in a Bayesian Belief Network fall under the following two categories:

1. The directed local Markov property: any variable is conditionally independent of its non descendents given its parents (Korb and Nicholson, 2003). This is known as the Bayesian Belief Network local dependence.
2. The second one is the global independence and is represented by concept of d-separation. The following definitions for d-separation are taken from (Korb and Nicholson, 2003: 42):

   Definition 1: '**d-separation** A set of nodes E d-separates two other sets of nodes X and Y if every path from a node in X to a node in Y is **blocked** given E'.

Definition 2: ‘**Blocked path** A path is blocked, given a set of nodes E, if there is a node Z on the path for which at least one of three conditions hold:

1. Z is in E and Z has at least one arc on the path leading in and one arc out (chain).
2. Z is in E and Z has both path arcs leading out (common cause)
3. Neither Z nor any descendent of Z is in E, and both path arcs lead in to Z (common effect)’.

The concept of d-separation is illustrated further later in this section. The directed global Markov property of a Bayesian Belief Network states that two sets of variables A and B are conditionally independent given a third set S, if S separates A and B in graph G (separates here denotes that all paths between A and B pass through S) (Korb and Nicholson, 2003).

The joint probability distribution, *P(X)* of the nodes is a product of the conditional probability distributions of the nodes in the Bayesian Network.

$$P(X) = \prod_{i=1}^{n} P(X_i \mid P_a(X_i)), \tag{3.1}$$

where $P_a(X_i)$ is the parent(s) of X_i which are the nodes in the Bayesian Belief Network.

Bayesian Belief Networks have been successfully used in a wide variety of fields and provide a good way of representing the independences in a domain in a graphical structure. The connections in Bayesian Belief Networks are all directed arrows, which can be interpreted as the direction of cause to effect (i.e. from the influencing node to the influenced node). Bayesian Belief Networks are referred to as directed acyclic graphs (DAGs) because of the directed edges they contain and their constraint that prohibits cycles in the graph. From a general perspective the two types of connections that you can have between any two nodes in a Bayesian Belief Network are as follows (please note that the following discussion on the connection types, is based on Koller and Friedman (2009: 69-71) and is an illustration of d-separation from which independency assertions can be made for a Bayesian Belief Network).

- Direct connection – This is the case where the two nodes *X* and *Y* are directly linked together. See Figure 3.4(a).

- Indirect connection – In this case the two nodes are not directly linked together but are indirectly linked together via a path (i.e. a path exists between them, in such a way that you can move between *X* and *Y*). See (Koller and Friedman, 2009) for an in-depth discussion of the four types of indirect connections that can exist in a Bayesian Belief Network. We briefly outline them below

- Indirect causal effect, this refers to the case where two nodes are indirectly linked via another node. The conditional independence property represented here is that *X* can influence *Y* via *Z*, as long as *Z* is unobserved - see the graph on the left of Figure 3.4(b). On the other hand if node *Z* is observed then *X* no longer influences *Y*, and the conditional independence statement that *X* is conditionally independent of *Y* given *Z* now holds (i.e. $X \coprod Y \mid Z$).

- Indirect evidential effect, this is very similar to the indirect causal effect with the difference that the direction of the connection is from *Y* to *X*, unlike in the case of the causal effect where it is from *X* to *Y* - see Figure 3.4(c). However as one of the properties of conditional independence is that it is symmetric, the conditional independence statement here is equivalent to that of the causal effect i.e. $Y \coprod X \mid Z$.

- Common cause, in this case both variables *X* and *Y* have a common cause (i.e. parent). In Figure 3.4(d), this common cause is represented by *Z.* Here, *X* can influence *Y* if the common cause *Z* is unobserved whilst if *Z* is observed $X \coprod Y \mid Z$ holds. This case is depicted in Figure 3.4(d).

- The final indirect connection type is the common effect, where *X* can influence *Y* via *Z* only if *Z* is observed or one of its descendents is observed. This particular case differs from the pattern seen in the other indirect connection types. Again it is depicted in Figure 3.4(e).

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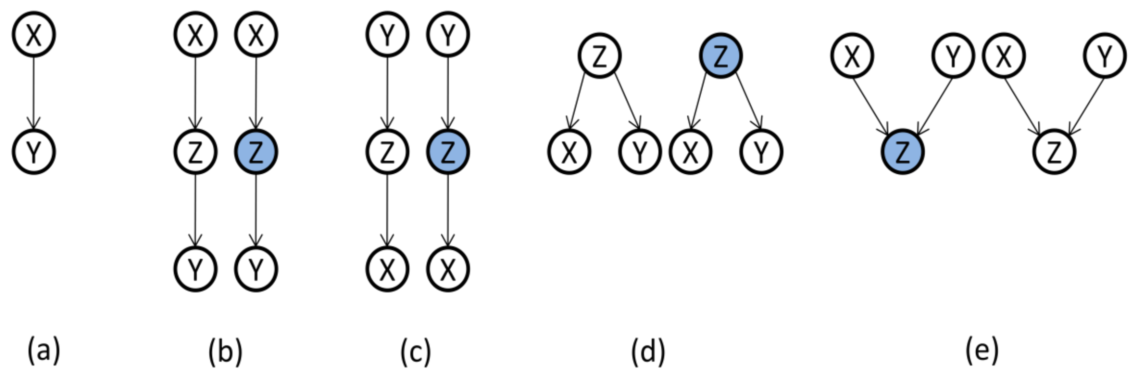


Figure 3.4: Summary of the possible connection types in a Bayesian Belief Network; shaded nodes represent observed nodes i.e. nodes where the value is known.

As mentioned earlier when classifying the different independencies that can be represented by a Bayesian Belief Network, they can broadly be split into two types, namely the local independencies which are represented in the joint distribution factorisation equation (see equation 3.1): every node is conditionally independent of its non-descendent nodes given its parents; and the global independencies (depicted in Figures 3.4(b) to (e)), which are formally outlined within the Bayesian Belief Network concept of d-separation, which can be used to compute all the conditional independences in the model. Further details on this can be seen in the works of Korb and Nicholson (2003) or (Koller and Friedman, 2009), who also provide, a precise and efficient algorithm for determining d-separation in a graph (pp74-75).

3.2.3 Bayesian belief networks and Risk Assessments

Risk analysis is characterised by uncertainty and lack of empirical data. As such, it may be necessary to use information based on subjective data such as expert opinion within the model. The ability of Bayesian belief networks to handle uncertainty and to allow the use of subjective data (known as the 'prior' within the model) is one of its distinctive advantages for use in risk assessments over other more traditional methods such as fault and event tree techniques. The prior probability is an estimate of the hypothesis in the absence of empirical evidence or complete empirical evidence, so humans have to give a judgement. An example of the use of a prior in the suicide mental health domain is the estimating of the probability of a person attempting suicide from experience or through the use of limited epidemiological information. Although Bayesian belief networks provide one of the proper ways of formalising subjective information, its critics are sceptical of the addition of subjective data to the model because it relies heavily on the assumption that subjective data included in the model are correct (Ferson, 2005). Mayo (1996) further argues that Bayesian belief networks do not provide the connection needed to empirical reality that characterises most of the sciences.

This controversy generated by the addition of priors in Bayesian Belief Network models cannot simply be brushed over because the selection of priors in a model often matters. For a Bayesian Belief Network model designer, issues such as what priors to choose, how to choose them and so on can be problematic. Advocates of Bayesian belief networks such as Jaynes (2003), argue that no matter the prior chosen, other data within the model would dominate the model results but, in practice, this is not always the case (Mayo, 1996).

Sentiments of sceptics of the use of priors in Bayesian Belief Network models are summed up in the following quote:

> "If the prior distribution at which I am frankly guessing, has little or no effect on the result why bother, and if it has a large effect, then since I do not know what I am doing how would I act on the conclusions drawn?" (Ferson, 2005:23)

However, the ability to add prior probabilities as inputs to the models is an extremely powerful feature, especially in areas like risk assessment where the bulk of data available might not be empirical data but subjective data. Proponents of Bayesian Belief Networks do not dispute the problems that could occur during the selection of priors but, rather, combat this by emphasising the importance of using sensitivity analyses when choosing priors (see Bernardo and Smith, 1994; Chan and Darwiche, 2004). These help by checking the influence of the priors and errors on the posterior.

Another perceived disadvantage often cited in the past regarding Bayesian belief networks is that they are computationally difficult; however, as a result of improvements in computer capacity, potential use of Bayesian belief networks in practical applications has increased (Korb and Nicholson, 2003). Despite the controversies accompanying the use of priors in Bayesian Belief Network modelling, it is universally agreed that the graphical nature of a Bayesian Belief Network makes it a powerful communication tool as it is intuitively understandable for humans. An example of research that has been done in the health domain using Bayesian belief networks for risk assessments can be found in Chun et al (2007) where the objective was to develop a 5-year breast cancer risk prediction model using Bayesian belief networks and compare obtained results to the Gail model, which is an established breast cancer risk model (Spielgelman et al, 1994). The specific method used was the Naive Bayes classifier. The preliminary results obtained showed that the Bayesian model appears to predict breast cancer risk better than the Gail model. Chun et al (2007) identified the novelty and advantages of Bayesian belief networks over other traditional risk prediction methods. They highlight the fact that Bayesian models represent progress in the area of risk prediction as they make it easier to integrate new evidence as and when it occurs. This view is one shared by several others including by Jianga and Mahadevan (2007).

3.2.4 Conclusion on Bayesian Belief Networks

The modelling approaches presented in this thesis have been successfully utilised in real world applications for risk assessments. However, the fact that the literature on the use of Bayesian belief networks for risk assessments is not as extensive as the literature on its use in other areas, such as machine learning and pattern recognition, highlights the fact that Bayesian belief networks for risk assessments is a growing area with scope for more research, innovation, expansion and sharing of ideas.

The advantages offered by the use of Bayesian belief networks for risk assessments by far outweigh the disadvantages and limitations that it has. With the progression of time, and the more the method is used in real world applications, the more it is being established as a valuable and powerful tool for risk analysis. This review also showed that some of the limitations of the method, such as concerns regarding the priors can be reduced by careful, thorough and systematic modelling. Furthermore, given the increasing utilisation of the method and scope for research into its usage in the area of risk assessments, there is the likelihood that resolutions to other limitations would surface in time.

Finally, regarding the different approaches that have been used for risk assessments using Bayesian belief networks, there is a need for a broadening of the methods used. An implication of having a wider range of methods is that it provides greater options, and this could lead to more appropriate choices geared towards effective models for risk assessment in specific areas and instances, as opposed to having generic but less effective models.

Having highlighted some of the advantages of using Bayesian Networks to implement a risk assessment model it can be seen as a potentially viable option in this thesis. However, as mentioned in Chapter 1 because of the particular semantics encoded in the GRiST knowledge structure i.e. the occurrence of both causal and non-causal relations within the knowledge structure, Bayesian networks or Markov random fields (to be discussed in the next section) alone do not provide the full solution. In the next section on Markov random fields it will also be seen that they with their lack of representation of causal relations fail to provide a full solution. Nevertheless it is important to note that although neither by itself provides a full solution, they each provide part of the solution in the form of the probability building blocks (this is discussed in further detail in Chapters 4 and 5).

3.3 Markov Random Field

Markov random fields, like Bayesian belief networks represent the joint probability distribution of random variables that they model (Kindermann and Snell, 1980). Also like Bayesian belief networks the variables in the domain being modelled are represented by the nodes in the Markov random field graphical structure, and the links between them represent interactions that exist between the different variables. However, for Markov random fields the links between nodes are not directed edges but undirected edges. This means that Markov random fields cannot model causal relations (i.e. links between nodes going from cause to effect). They are used to model symmetric and associative relationships between variables. A Markov random field can be formally defined as a Graph *G* of the form:

$G=(V,E)$; if $(x,y)\in E$ then $(y,x)\in E$

The joint probability of a Markov random field is a product over functions of the maximal cliques in the graph, where maximal cliques are sub graphs that are fully connected (Buntine, 1994).

$$p(X)=\prod_{C\in Cliques(G)} f_C(C)\,. \tag{3.2}$$

Where C represents cliques, G the Markov random field graphical structure, X the nodes in the Markov random field and f_c function over the maximal cliques in the structure.

An example is depicted in Figure 3.5 which has three maximal cliques (i.e. every node in the sub graph is connected). The first maximal clique is the sub graph that consists of nodes a, b, e and f, the second maximal cliques nodes b, c, f and g and finally the third maximal clique nodes c, d, g and h. The factorisation of the joint probability is:

$$p(a,b,c,d,e,f,g,h)=f_1(a,b,e,f)\,f_2(b,c,f,g)\,f_3(c,d,g,h)\,.$$

From the formula for the factorisation of the Markov random field joint probability we see that each node is conditionally independent of its non-neighbours given its neighbours. If we consider node b from Figure 3.5 for instance, we see that it shares at least one function with all its neighbours (a, e, f, c and g) and shares no functions with its non-neighbours (d and h).

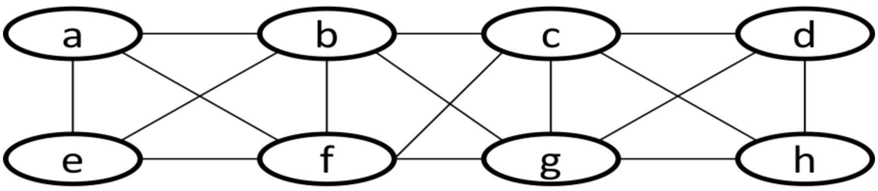


Figure 3.5: A simple Markov random field (adapted from Buntine, 1994:163).

Unlike in Bayesian belief networks where the parameters within the graph that give the strength of influences between nodes are probabilities, for Markov random fields they are not probabilities but are represented by functions between linked nodes known as factors (Koller and Friedman, 2009). However, from equation (3.2) that defines the factorisation of a Markov random field, it can be seen that the probability of a state is equal to the product of the functions of the maximal cliques in the graph.

3.3.1 Markov Random Field and their Markov Properties

The Markov properties of a Markov random field define the kinds of conditional independence that can be modelled by a Markov random field. The following definitions taken from Kindermann and Snell (1980) and Koller and Friedman (2009) represent the three main categories of Markov properties:

Pairwise Markov property: Any two non-adjacent variables are conditionally independent given all other variables:

$$X_u \coprod X_v \mid X_{V|\{u,v\}} if \{u,v\} \notin E. \tag{3.3}$$

Local Markov property: A variable is conditionally independent of all other variables given its neighbours:

$$X_v \coprod X_{V \backslash cl(v)} \mid X_{ne(v)} \,. \tag{3.4}$$

where ne(v) is the set of neighbours of v, and cl(v) = $\{v\} \cup$ ne(v) is the closed neighbourhood of v.

Global Markov property: Any two subsets of variables are conditionally independent given a separating subset:

$$X_A \coprod X_B \mid X_S \,. \tag{3.5}$$

where every path from a node in *A* to a node in *B* passes through *S*.

These definitions of conditional independencies are different from that of the Bayesian belief networks where the use of d-separation was used to define the conditional independencies of the directed graph. It is generally easier to determine the conditional independencies of Markov random fields.

The use of Markov random fields as a part of the solution to the implementation of the GRiST chain graph came about as a direct result of the semantics ingrained in the GRiST knowledge structure. This was particularly significant because of the correlation between part of the GRiST knowledge structure and the Markov random fields properties. In Chapter 5 the ways and circumstances under which these correlate and map to the different parts of the GRiST component structures are examined.

One of the advantages provided by Markov random fields for the mapping from the non causal sections of the GRiST knowledge structure is the fact that it is good for context dependent modelling (Bouman, 1995). This implies modelling the non causal parts of the GRiST knowledge structure that are generic in nature (i.e. they can occur in more than one location) with Markov random fields will be an expedient design choice. This further implies that the modelling of the generic nodes occurring in more than one location in the model would not be a problem. In Markov random fields nodes are only dependent on their direct neighbours and as such the generic nodes would be only dependent on the nodes directly linked to them and these would be the same regardless of their location in the model, for example *Depression* would always have the same structure i.e. the same direct neighbours regardless of which location it is in. This ability of Markov random fields to model local dependencies is a great advantage for the modelling of the GRiST non causal relations.

3.4 Chain Graphs

Having reviewed Bayesian belief networks and Markov random fields for the reasons mentioned earlier, it can be seen that neither graphical model can fully adequately be used to model the GRiST knowledge structure, this assertion is further justified in Chapter 4 where the GRiST semantics are further explored. Hence the decision to use chain graphs. However, it should be noted that as chain graphs combine the mathematical properties of both Bayesian networks and Markov random fields, these two graphical models individually make up the possible probability building blocks to which the component structures of the GRiST knowledge structure can be mapped to (these properties will be discussed in-depth in Chapter 5). These probability building blocks are then used to implement the final chain graph.

In the literature these kinds of graphs (i.e. hybrid graphs with both directed and undirected links between variables) are known as chain graphs. It has also been noted that active research is currently being done in various domains using / attempting to use chain graphs. This is because they allow complex domains to be modelled using a combination of both causal and associative relationships between nodes. Some of the previous work that has been done using chain graphs includes:

- the use of graphical chain models for investigating the complex structure of a psychological disease (pathological gambling) (Clelia and Biffi, 2004);
- The determinants of infant mortality (Mohamed et al, 1998);
- selecting and fitting graphical chain models to longitudinal data (Borgoni et al, 2004);
- protein classification (Carroll and Pavlovic, 2006);
- a new approach to argument by analogy (extrapolation and chain graphs) (Steel, 2008).

The above examples illustrate the use of the graphical structure to represent domains containing both causal and non causal relations, which is the desired outcome for the GRiST structure. In the examples it is also seen how these knowledge structures are used to infer probabilistic distributions and other relevant information, for instance, Mohamed et al (1998) use chain graphs to identify the causal factors leading to infant mortality. This section continues by discussing chain graphs and their properties. Chain graphs are graphical models, which allow both directed and undirected graphs with the constraint that they do not have semi-directed cycles (semi-directed cycles refers to the constraint that all arrows within any cycle must point in the same direction) (Drton, 2009).

The conventional way to represent the structure of a chain graph is to partition the nodes of the graph into subsets known as blocks, with the explanatory nodes in blocks at the right hand and the response nodes on the left and the intermediate nodes in the centre (Bouckaert and Studený, 1995). The blocks in the chain graphs, however do not have to be explicitly drawn in chain graphs. An example of this adapted from Blauth and Pigeot (2000) can be seen in Figure 3.6.

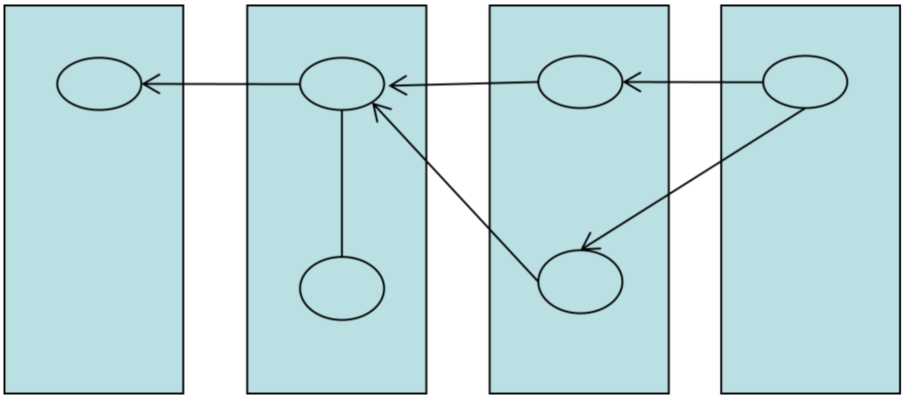


Figure 3.6: Graphical Chain Model adapted from Blauth and Pigeot (2000).

The directed links (arrows) and undirected links (lines) within a chain graph represent the conditional independence and dependence relations between the variables in the graph. The Markov properties of a graph formally define the conditional independence relations that exist in the graph.

The following adaptation from Edwards (2000) illustrates the factorisation of the joint density of chain graphs and the pairwise Markov property. If a chain graph consists of subsets $S_1, S_2, ..., S_n$ and the variables across all *n* subsets (blocks) are labelled $X_1, X_2, ..., X_i$. Then the factorisation of the joint density of the variables is

$$f(X_1, X_2, ..., X_i) = f(S_1) f(S_2 \mid S_1) .... f(S_n \mid S_1 \cup S_2 \cup S_{n-1}). \qquad (3.6)$$

In the above block S_1 will contain variables that are pure explanatory variables whereas the block S_n will contain pure response variables. Furthermore the absence of a line (i.e.

symmetric relation) between any two variables (V_1 and V_2) within a particular subset S_n or the absence of a directed link between two variables V_1 and V_2 of two different subsets (S_{n-1} and S_n) based on the pairwise Markov property of chain graphs implies

$$V_1 \coprod V_2 \mid S_1 \cup S_2 \ldots S_n. \tag{3.7}$$

That is two variables are conditionally independent given all prior and concurrent variables.

3.4.1 Chain Graphs and their Conditional Independencies

This section on the conditional independencies of a chain graph is based on the discussion by Koller and Friedman (2009). Each chain graph component C_i (which is equivalent to a chain graph block structure) is associated with a conditional random field that defines the conditional probability of *P(*C_i*|Parents(*C_i*))*. A conditional random field is an undirected graph that encodes the conditional distribution *P(Y|X)*, where *X* is observed and *Y* is unobserved.

The interpretation of the independencies represented by a chain graph fall into three general categories (the following definitions are taken from Koller and Friedman, 2009).

- Chain graph pairwise independencies

  $$I_p(CG) = \{(X \coprod Y \mid NonDescendents_X - \{X,Y\})\}: \tag{3.8}$$

  X,Y non-adjacent, Y $\in NonDescendents_X\}$

  Any two non-adjacent variables are conditionally independent given their non descendent variables.

- Chain graph local independencies

  $$I_l(CG) = \{(X \coprod NonDescendents_X - Boundary_X \mid Boundary_X) : X \in x\}: \tag{3.9}$$

  A variable is conditionally independent of all other non descendent variables (minus its boundary variables) given its boundary variables.

- Chain graph global independencies

The global independencies are defined using the concept of moral graphs and c-separation (see Koller and Friedman (2009) for more details). A chain graph is moralised by connecting all nodes that are elements of *Parents*(C_i) and then converting all directed edges to undirected edges. A moral graph is used to convert a directed graph into its equivalent undirected graph by adding a link between all nodes that have a common child but are themselves not linked together.

As mentioned by Edwards (2000) for chain graphs the main modelling challenge is being able to find a correct model for each of the subsets. Something that helps simplify to an extent the entire modelling process for the chain graph is the fact that in a similar vein to directed graphs the manner in which each block is modelled is independent of the modelling choices for other blocks and as such the entire chain graph can be modelled in a structured manner, dealing with one subsection at a time (Edwards, 2000). This is ideal for GRiST where the idea of subsections is ingrained into the structure. For instance, the GRiST domain is made up of different locations which are made up of components comprising of concept and datum nodes.

3.5 Factor Graph

A factor graph consists of a set of variables, factors and edges connecting the variables to factors. In the actual graph, each variable is represented by a round node whilst each factor is represented by a square node. The joint probability of the variables in a factor graph is a product of all the factors in the factor graph [34, 49] and the factor graph functions represent a term in the joint distribution factorisation (Frey, 2003).

$$fg(X_1, X_2, ..., X_n) = \prod_{j=1} f_j(S_j). \text{ All possible subsets are considered.} \quad (3.10)$$

Where *f* refers to the factors, S_j a subset of ($X_{,}, X_2, .., X_n$) and j represents a set of indexes (Kschischang et al, 2001).

In a factor graph, function nodes are only connected to variables that they depend on (Bauke, 2008). For example the factor graph represented in Figure 3.7 can be expressed as the product;

$$fg(w, x, y, z) = f_A(w) f_B(x) f_c(w, x, y) f_D(y, z). \quad (3.11)$$

In both this equation and in Figure 3.7 it can be seen that each of the function nodes is only directly joined to the variables it depends on.

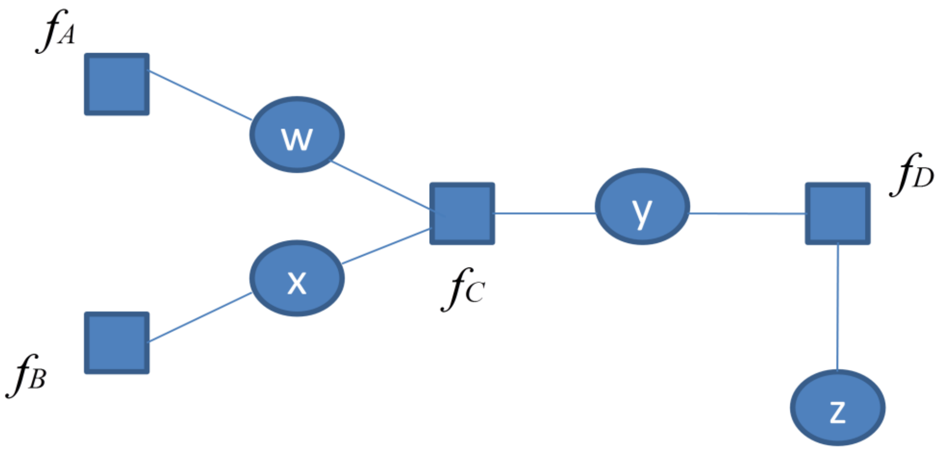


Figure 3.7: A factor graph.

The rationale behind our usage of factor graphs is twofold. The first reason was that both of the possible probability building blocks (i.e. Bayesian belief networks and Markov random fields) that can be obtained from the mapping process can be easily converted into factor graphs. This is partly because all three graphical structures (i.e. Bayesian belief networks, Markov random fields and factor graphs) inherently model within their structures the joint probability distribution of their constituent random variables (Kschischang et al, 2001). In addition to this factor graphs can also be used to represent the same conditional independencies as that of any Bayesian Belief Network, Markov random field or chain graph, and this ensures that there is no semantic loss as a result of any conversions to factor graphs (Frey, 2003). Our second motivation for converting to factor graphs is that the conversion opens up the way for application of the highly effective inference sum-product message passing algorithm to our probabilistic model to obtain the required mental health risk assessments (Kschischang et al, 2001).

3.5.1 The Factor Graph Structure

The conversion process from Bayesian belief networks, Markov random fields and chain graphs to factor graphs is now briefly outlined. For more details on factor graphs see Kschischang et al (2001).

3.5.1.1 Conversion of Bayesian Belief Network to Factor Graph

To convert from a Bayesian Belief Network to a factor graph, the following steps need to be followed

- Add a factor graph function between every node and its parents. In this context the factor graph function corresponds to the conditional probability of the node given its parents (Frey, 2003).
- For nodes without parents add a factor graph function before the node. In this setting the factor graph function represents the marginal distribution of the variable corresponding to the node to which it is attached to (Frey, 2003).

Figure 3.8 is an example of the conversion of a Bayesian Belief Network (left side of figure) to a factor graph (right side of figure). So in GRiST component structures that on applying the mapping rules, map to Bayesian Belief Networks, will in turn be converted to factor graphs using this technique.

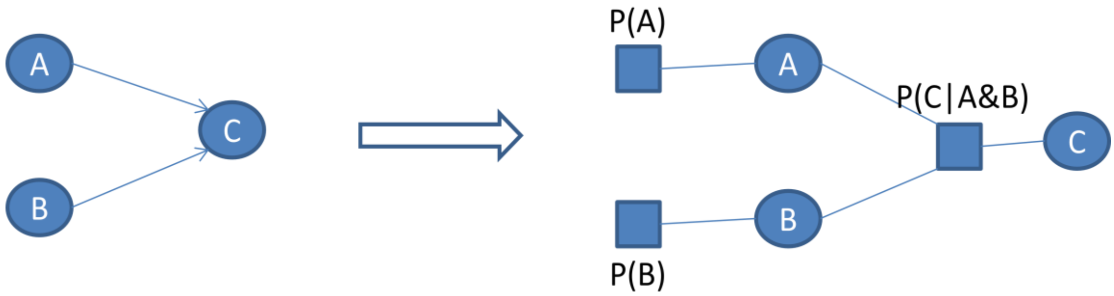


Figure 3.8: A Bayesian Belief Network and its equivalent factor graph.

From Figure 3.8 we see that for the conversion from a Bayesian Belief Network to a factor graph, the factor graph function corresponds directly to the Bayesian Belief Network notion of $P(X \mid Pa(X))$ i.e. the probability of *X* given the parents of *X*.

3.5.1.2 Conversion of Markov random field to Factor Graph

For the conversion from a Markov random field to a factor graph, unlike in the Bayesian Belief Network, the conversion process takes into account whether or not a variable is observed. For the conversion from Markov random field to factor graph, functions are created for every clique in the Markov random field and these functions are equal to the potential function of the maximal cliques of the nodes in the Markov random field (Frey, 2003). Potential functions for discrete domains can be represented by tables and multiplying their cells gives the joint probability of the model (see Jordan (1997) for further details).

The conversion steps are as follows:

- Every observed variable is replaced by a factor graph function;
- Every unobserved variable is represented by itself (i.e. it is left untouched);
- A factor graph function is added between any two unobserved nodes directly linked;
- A factor graph function is added to every single unobserved node.

Figure 3.9 shows examples of two Markov random fields' conversions to factor graphs. In the figures observed nodes are shown with broken lines.

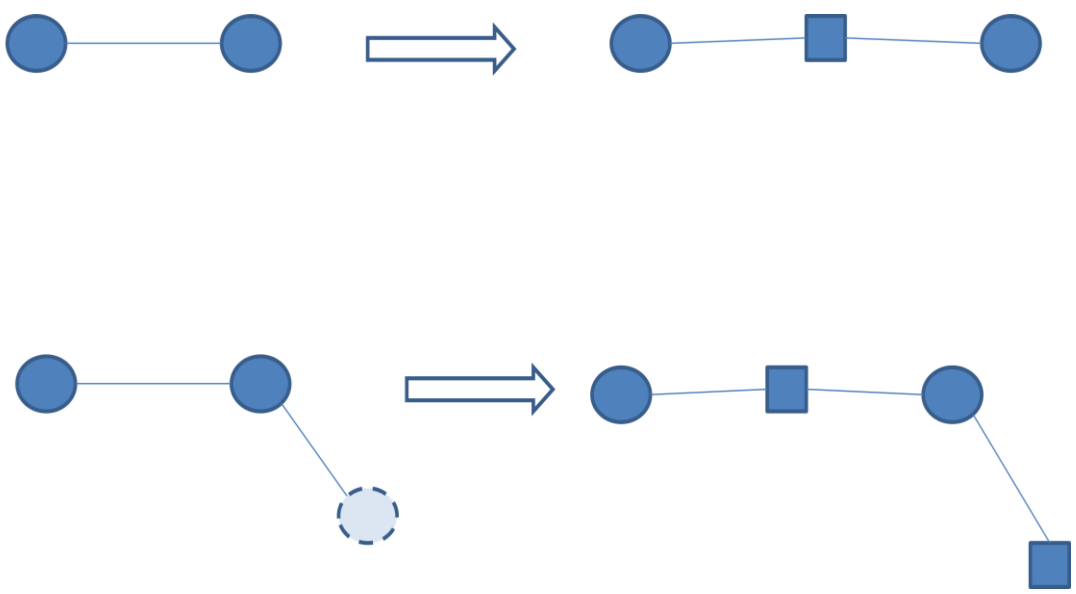


Figure 3.9: Markov random fields and their equivalent factor graphs (observed nodes are shown with broken lines).

Further details on the Markov random field to factor graph conversion can be seen in Kschischang et al (2001), Yedidia et al (2003) and Gillies (n.d.).

3.5.1.3 Conversion of Chain Graph to Factor Graph

In the conversion of the GRiST chain graph to a factor graph prior to the inference stage we combine the rules for conversion for both Bayesian belief networks and Markov random fields discussed above to obtain a set of rules that will make possible the required conversion. As the Markov random field structures (i.e. the variables with symmetric relations between them), are contained within separate distinct blocks within the chain graph, the plan is to convert to factor graphs these structures using the Markov random field to factor graphs independently of the rest of the chain graph. After these have been converted to chain graphs the directed links (i.e. the variables with the Bayesian Belief Network structure), would then be converted to factor graphs using the Bayesian Belief Network to factor graph conversion rules. All this will then culminate in the conversion of the GRiST chain graph to a factor graph. Figure 3.10 illustrates the above process.

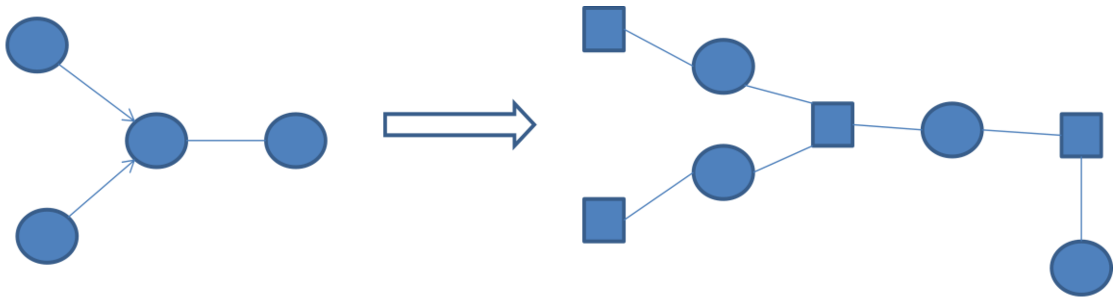


Figure 3.10: A chain graph and its equivalent factor graph.

Two algorithms that can be used to perform inference on factor graphs are the sum–product algorithm and the belief propagation algorithm. A highly detailed description of the sum-product algorithm is given by Kschischang et al (2001) and Yedidia et al (2003) contains a detailed discussion for the belief propagation algorithm on factor graphs. For the GRiST factor graph inference the sum-product algorithm was used because it works very well with factor graphs and is described in Chapter 6.

3.6 Conclusion

In this chapter various properties of the probability building blocks that are used in the development of the final GRiST probabilistic model have been discussed. These will be built on in subsequent chapters. In the next chapter (i.e. Chapter 4) the GRiST visualisations and the various relationship types that exist between the various nodes within the GRiST knowledge structure are explored and how these impact on the development of the final GRiST probabilistic graphical model is considered.

Chapter Four

4. The GRiST Visualisations and Relationship Types

This chapter discusses and builds on the exploration of the different visualisations of the GRiST knowledge representation structure started in Chapter 2. The aim is to ensure that the GRiST knowledge structure is decomposed into a correct and fully exhaustive list of different components that can be later mapped to probability building blocks. As such every section in this chapter is geared towards this main objective of distinguishing the types of concepts that help determine the most appropriate probability structure for conversion. The specifics of the representations (i.e. fuzzy model/expertise, ontologies and the eventual class/objects) are outlined and the relations that exist between the GRiST variables are also discussed.

Chapter 2 explored how the GRiST fuzzy model was composed of three constituent component structures but this was motivated mainly by how the expert model could be more easily managed during its construction and evolution. Closer examination of the structures showed that they represent potentially different types of relationships, which resonated with the work on ontologies in computer sciences. Hence the decision was made to re-explore the GRiST knowledge structure from the ontological perspective to determine whether more granular decomposition could usefully inform probabilistic relationships. In addition to the ontology angle, the semantics inherent in the GRiST knowledge structure are also examined from the classes/objects perspective. Identification of the correlations and differences between the various representations (i.e. the GRiST fuzzy model, the ontological and the classes/objects representations) and their properties is also carried out. This is all done in a bid to identify the structures from the GRiST knowledge structure that are most useful for mapping to the probability graphs. Figure 4.1 illustrates how the various sections of this chapter relate to each other and to the overall objective of the identification of the best GRiST component structures to map to the most appropriate probability building blocks.

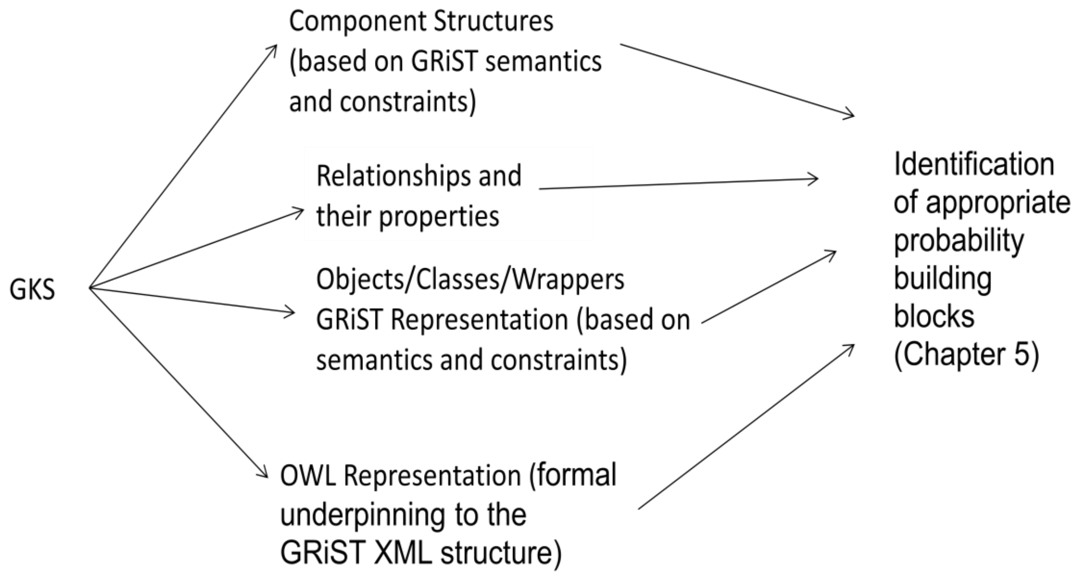


Figure 4.1: Overview of the chapter (GKS denotes GRiST knowledge structure).

4.1 The GRiST Ontology

In this section the GRiST knowledge structure is examined from the standpoint of an ontological representation. A discussion is carried out on the possible implementation and representation of a GRiST ontology starting from the very beginnings of the development of the GRiST knowledge structure. The original knowledge elicitation process from the experts was done through the use of interviews, online tasks and focus groups. These were then encoded using mind maps (Buzan, 1991), and over several iterations of the Delphi method (Linstone and Turoff, 1975), final mind maps that encapsulated the general consensus reached by the experts were produced. These mind maps were in XML file format to facilitate computer processing and represented a formal specification of a hierarchical tree structure, as depicted in Figure 4.2.

The entire process resulted in the representation of the risk factors that the experts considered most important for various top risks in a hierarchical tree form. The hierarchical representation encompasses both the risk factors and the connections (depicted via links) between them.

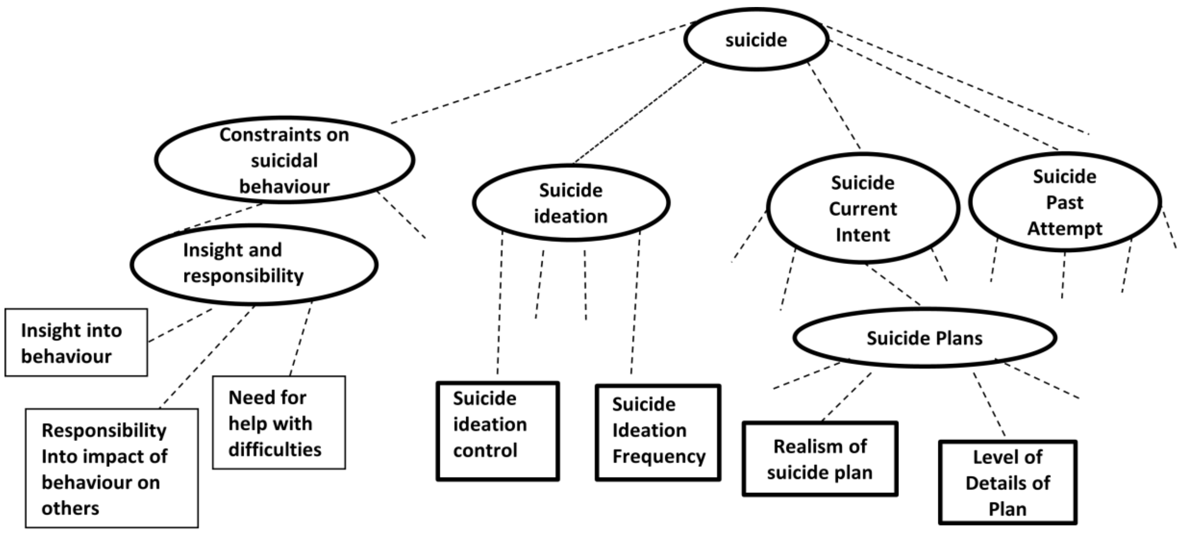


Figure 4.2: Illustration of a subsection of the GRiST knowledge structure in a hierarchical tree form.

However, the GRiST knowledge structure does not explicitly define the relationship types between the various nodes linked together and as our main objective is to map the GRiST knowledge structure to an equivalent probabilistic graphical model, a first step to achieving this will involve the defining of the exact relationship types between the various nodes. The mind maps simply state the hierarchical relationships but not any finer distinction such as a precise definition of the relations between nodes, class/object membership or causality.

As a starting point to the exploration of the development of a GRiST ontology and the relationships present in the structure, the GRiST knowledge structure representation is extended into the form of concept maps (Novak and Cañas, 2008). This extension is done via the addition of explicitly defined relationship types between all nodes in the GRiST knowledge structure that are connected in one way or another. A concept map differs from a mind map in that not only does it depict links between connected variables in a domain but it also explicitly defines the relationship between variables. For example in a concept map depicting a family tree, each pair of connected nodes would have an explicit relationship defined between them e.g. *mother of*, *brother of* and so on. A concept map is a knowledge representation technique that depicts both the variables within a domain and the relationships that exists between these variables (Novak and Cañas, 2008). We use these concept maps as a starting point to explore a possible GRiST OWL ontology which is a web ontology language which aids the description of variables in a domain and the relationships that exist between them. The main objective is to aid and help validate our decomposition of the GRiST knowledge structure into component structures. These component structures are then mapped to probability building blocks, which will make up the final GRiST probabilistic graphical model.

The defining of the relationship types between the nodes is not important for the original fuzzy GRiST model. However, it is relevant for the mapping to the probabilistic graphical model. The addition of the relationship types for the development of the ontology is therefore an extension to the GRiST knowledge structure. Within the GRiST fuzzy model the nature of the relationship types are also not defined i.e. whether they are causal or not and where they are causal, the direction of causality. For example in Figure 4.7, *mental health* is an established causal risk factor of *suicide* but is represented in the same way in the GRiST knowledge structure as for instance *gen-cog-think-mem* (thinking processes and memory) to *gen-impaird-cog* (impaired cognitive function) which are not causally related. However, in probabilistic graphical models, causality can be taken into account in both the structure of the graph and subsequently in the inference algorithms used within the model.

4.2 GRiST Relationship Types and Concept Maps

In this section the mapping of the GRiST knowledge structure to facilitate the clear defining of all possible relationship types between the various GRiST knowledge structure nodes is discussed. After this an exploration is done on a possible GRiST ontology. The generation of the structural aspects of the required concept maps from the GRiST knowledge structure follows on from the existing knowledge structure. This is because to develop the concept map, the extension needed is simply the addition of the relevant relationship types between the various nodes. Concept maps are hierarchical and model the knowledge representation of a domain with the relationship types between nodes explicitly defined. The GRiST knowledge structure is like a concept map without the relationship types defined, so the initial challenge is the defining of the relationship types between the nodes.

4.2.1 Relationship Types from Other Ontologies

It is often a good starting point when embarking on a journey to consider and learn from the experiences of those who have gone ahead of one, and as such we began the process of defining the relationship types that exists between the various nodes in the

GRiST knowledge structure by examining previous related work that has been done on various types of relationships that can exist between nodes in an ontology or concept map in the mental health domain and other related domains. Many different relationship types have been defined and used in numerous ontologies such as the Open Biomedical Ontologies OBO (Smith et al, 2005), other biomedical ontologies (Schulz et al, 2006; Rubin et al, 2008), gene ontology (The Gene Ontology, n.d.), and ontology based modelling of breast cancer (Abidi, 2007; Hu et al, 2007).

Listed in Table 4.1 are a few examples of relationship types that have been identified from general medical and mental health ontologies:

Table 4.1: Some relationship types and their source domains

Relationship Type	**Source Domains**
has_focus	Psychosis Ontology (Kola et al, 2010)
has_cause	Psychosis Ontology
is_a_type_of	Psychosis Ontology
hasPart	Ontology of Mental Disease (Ceusters and Smith, 2010)
part of	Ontology of Mental Disease, Biomedical Ontologies (Smith et al, 2005)
has Agent	Ontology of Mental Disease, Biomedical Ontologies
hasParticipant	Ontology of Mental Disease, Biomedical Ontologies
ParticipantOf	Ontology of Mental Disease
manifestationOf	Ontology of Mental Disease
inheresIn	Ontology of Mental Disease
inheresOf	Ontology of Mental Disease
Bodily Feature	Ontology of Mental Disease
isAbout	Ontology of Mental Disease
realisationOf	Ontology of Mental Disease
specificallyDependsOn	Ontology of Mental Disease
is_a	Biomedical Ontologies
located_in	Biomedical Ontologies
contained_in	Biomedical Ontologies

adjacent_to	Biomedical Ontologies
transformation_of	Biomedical Ontologies
derives_from	Biomedical Ontologies
preceded_by	Biomedical Ontologies

The relationship types between nodes in the various ontologies are defined from the nature of the association between the nodes. So, for instance, where the relation between two nodes is a class to subclass relation, this is represented by an *is-a* relation. Smith et al (2005) detail ways to avoid errors in the defining of the relations by the use of logic and explicit formal definitions. Some examples of the definitions that are given for a few relationship types between nodes for the biomedical ontologies taken from Smith et al (2005) are:

- X *is_a* X_1 : Every X is at the same time a X_1
- X *part_of* X_1: Every X at any time, is part of X_1 at the same time
- X *preceded_by* X_1: Every X is such that there is some earlier X_1

However, the definitions of a number of these relationship types overlap even though they have been given different names in different ontologies. In some domains, to expedite collaborations and reduce the likelihood of people trying to re-invent the wheel, work is being done on developing standards that will ensure everyone within said domains use uniform names and definitions (Schuurman and Leszczynski, 2008).

In addition to the definition of the various relationship types, Smith et al (2005) also identified the properties of each type of relationship i.e. whether or not they are transitive, symmetric, reflexive or antisymmetric. The importance of this classification of the properties of the relationship types in this research becomes more apparent later during the exploration of the issue of causality.

The identification of the GRiST relationship types has been carried out in a similar manner to that of other ontologies. The relationships between nodes are defined to mimic the situation in the actual domain. So, if for example in the mental health domain node X_1 is known to cause node X_2, then in the GRiST concept map, a relationship that reflects this causal relationship is used.

The following main relationships within the GRiST knowledge structure were identified by examination of the knowledge domain with a domain expert as part of this research:

- *is_a*
- *gives_details_of*
- *precedes*
- *contributes_to*
- *part_of*
- *component_of*

The explicit definitions given to each of these are as follows:

- X_1 *gives_details_of* X_2 – Every X_1 provides more details about X_2, thereby adding clarity to the semantic definition of X_2. X_1 is always a part of X_2 but does not have a causal effect on it. GRiST examples include *impaired cognitive function* and its sibling node *learning disabilities* which both give more details about the concept *mental faculties/cognitive capacity* (see Figure 4.5).
- X_1 *is_a* X_2 - The definition here is the same as in other similar ontologies such as in Smith et al (2005), where every X_1 is an X_2. GRiST examples include *physical indicators of suicide* and its internal nodes (i.e. suic-phy-indic, sn-appearance and gen-sh-cuts in Figure 5.1).
- X_1 *precedes* X_2 – Again this has the same definition as in other ontologies. X_1 must always happen before X_2. GRiST examples include the *suicide past attempt* concept and the *suicide* concept.
- X_1 *contributes_to* X_2 – Every X_1 contributes directly to both the semantic meaning and uncertainty values of X_2. GRiST examples include the concept *gen-personality* (see Figure 4.5) and its internal nodes. In some instances it is used where at first glance the *is-a* relationship might be expected. For example for the *gen-feelings-emotion* concept, the value of internal nodes *anger*, *jealousy, anxieties* and so on, make up the final state of the person's emotions / feelings. Initially this was originally modelled using an *is-a* relationship, the logic being that they are all types of emotions. However, in the GRiST knowledge structure these nodes are not mutually exclusive and a person can have values for all of them which all taken together define the current state of the person's emotions, hence the change from the *is-a* relationship type to the *contributes_to* type. This means that in the GRiST knowledge structure the state of a person's emotion is not determined by answering the question 'is the person angry or jealous or anxious and so on?' but rather by answering the question 'how much anger is the person feeling and in addition to this anger, how anxious is the person feeling and likewise for the

various emotions?'. It is this difference in the questions that formulates the relationship type *contributes_to*.

- X_1 *part_of* X_2 – This again is similar to the definition found in some other ontologies. For instance from Smith et al (2005), here every X_1 at each point in time is part of X_2. Although this definition is similar to the *gives_details_of* relation, it differs from it in that X_1 is always contained in X_2 regardless of its location or context. This has an impact on the way they are represented in the mapping to the probability graphs.
- X_1 *component_of* X_2 – This is similar to the *part_of* relation but the difference here is that instead of every X_1 always being part of X_2 in this case we have X_1 sometimes being part of X_2. This additional relation was specifically required because of the way the GRiST knowledge structure is modelled**.** An example of this is the depression concept (see Figure 4.7) which always contains *gen-voice-hal,* but *gen-voice-hal* appears in other concepts as well (which violates the *part_of* relationship constraint). This distinguishing factor becomes significant when it comes to mapping to the relevant probability graphs and is discussed in more depth later.

Having defined the relations, it is useful, in a similar manner to Smith et al (2005), to identify their properties, which are summarised in Table 4.2.

Table 4.2: The GRiST relations and their properties

Relation	**Transitive**	**Symmetric**	**Reflexive**	**Antisymmetric**
gives_details_of	No	No	No	No
is_a	Yes	No	Yes	Yes
Precedes	Yes	No	No	No
contributes_to	Yes	No	No	No
part_of	Yes	No	Yes	Yes
component_of	Yes	No	No	No

A brief definition of each of the properties is given; this is followed by an in-depth discussion on how these relate to causality in subsequent sections.

- Transitive: For a relation to be termed as being transitive the following must apply. If there are three variables X_1, X_2 and X_3 and the said relation is represented by *R*. If $X_1 R X_2$ and $X_2 R X_3$ then $X_1 R X_3$.

- Symmetric: Two variables X_1 and X_2 are said to have a symmetric relation with each other if If $X_1 R X_2$ directly implies that $X_2 R X_1$. An example is the relationship of brotherhood between two men, if X_1 *is brother to* X_2 then it directly follows that X_2 *is brother to* X_1.

- Reflexive: A relation is said to be reflexive, if and only if every element is related to itself via the relation. For example the "equals to" relation is reflexive, as every element X is equal to itself.

- Antisymmetric: A relationship is antisymmetric if $R(X_1,X_2)$ and $R(X_2,X_1)$ can both hold only if $X_1 = X_2$. This implies that distinct variables are never both related to each other, so if $R(X_1,X_2)$ and $R(X_2,X_1)$ holds then X_1 and X_2 cannot be distinct variables but must be equal to each other (i.e. the same variable).

Using the GRiST relationship definitions and their properties an exploration of the relationship between these relationship types and causality is now carried out. Later on in Chapter 5 this identification of causal and non causal relations plays a role when it comes to the mapping from the GRiST knowledge structure to the probability building blocks.

4.2.2 Causality and Relationship Types

In probabilistic graphical models there is a difference in how associations between nodes that are causal/non causal are represented. This difference in the representations impacts directly on the choice of probability graphical models that a component structure maps to and the inference algorithms used on the models. This in turn then directly impacts on the probability values (risk assessments) that will be obtained from the probabilistic graphical model.

To ascertain causation, a set of criteria were listed by Hill (1965) known as Hill's Criteria, which Hill terms viewpoints. These include:

1) Strength – this criterion relates to the strength observed between the associations of the variables in question. The premise being that the greater the strength of association the more likely that the relationship is causal. Strength can be measured or observed in different ways primarily based on the variables being

observed. For the GRiST variables, the measurements could be based on the uncertainty values (e.g. correlation values between variables, different forms and levels of associations between variables). By correlations here the reference is to the measure of dependence between nodes.

2) Consistency – How consistently is this association observed? Is it a one-off observation or seen many times? In GRiST for example where correlation values are taken for generic concepts, are the level of correlations seen between a particular set of nodes in different locations in the model consistent?
3) Specificity – The more specific the observed association between the variables, the more likely the relationship is to be causal. That is, the greater the association (in the sense that the observation is as a result of interaction between the variables of interest and not some other external factor) between the variables the higher the probability that the relationship is a cause to effect one. For example, if this criterion holds between serious depression and suicide (or attempted suicide), then the rate of suicide (or attempted suicide) among people who suffer from serious depression should be higher than among those who do not.
4) Temporality – This refers to the order of occurrence of the variables. Does X_1 cause X_2 or does X_2 cause X_1? Hill points out that in observing the cause and effect variables, the cause must always necessarily (and logically) precede the effect.
5) Biological Gradient – This refers to the expectation that generally the greater the value of the causal element the greater the observed effect. In GRiST where the maximal contributing risk factors for each top risk is modelled, it will be expected that the greater the uncertainty values of these contributing risk factors, the higher the risk assessments values obtained for the top risk. And for causal elements of the model, this will be expected to be seen in correlation analysis performed on the data. However, for the GRiST knowledge structure the biological gradient is built into the semantics of GRiST independently of causality and as such this criteria is not particularly useful as a standalone criteria.
6) Plausibility – Is the cause to effect relation that we suspect plausible? It should be noted that Hill comments on how this should not be an absolute requirement for causality. Because at each point in time the current notion of what is plausible is limited by the knowledge available at that particular time in history. He goes on further to give some potent examples from the past to illustrate the point that even though some observations might seem new to what is currently accepted as right, care should be taken not to dismiss such ideas flippantly.

7) Coherence – This refers to the flip side of plausibility, the level of coherence with currently accepted knowledge. Again, like plausibility it cannot be seen as an absolute requirement, but it is possible that in a rare case (but not generally) it might highlight an inconsistency in currently accepted knowledge. Plausibility can be seen as a subgroup of coherence.
8) Experiment – This refers to the use of experiments to validate or uncover causality. For GRiST this is seen in the correlation analysis and statistical tests carried out on the data obtained during clinical use of the tool.
9) Analogy – The use of observation and effects from similar circumstances.

In the quest to identify which of the GRiST relations are causal, these identified criteria are used as guidelines and check criteria. Next, the possible correlations are explored between the relation properties (i.e. transitive, symmetric, reflexive and antisymmetric) and the semantics contained in the relationship definitions with causality. This is being done in a bid to see whether this exploration can help in the determination of which relations in the GRiST knowledge structure are intrinsically causal and which are not.

4.2.3 The Relationship Properties, Causality and Conditional Independence

As seen earlier, in addition to giving each of the GRiST relations a precise definition, we also considered some of the possible properties of these relations (see Table 4.2). In this section these properties are explored further. In particular an exploration is carried out to make conclusions with regards to causality from the examination of the properties of the relations and their inherent semantics.

In Chapter 5, more in-depth exploration of the potential impact of these relationship links on their Markov properties will be done. For a probability graphical structure its Markov property represents its conditional independence statement. This is important because the Markov property of the eventual probabilistic graphical model that the GRiST knowledge structure maps to, will determine the conditional independence properties that will be represented in the model. Recall that the overall objective is the correct mapping of the GRiST knowledge structure to an equivalent probabilistic graphical model. A correct mapping will mean that the conditional independence properties contained within the GRiST knowledge structure and its ingrained semantics are correctly represented in the probabilistic graphical model. Whether this is achieved or not will be determined by the Markov properties of the probabilistic graphical model.

The relationship between causality and conditional independence is one that has been examined by various researchers (Chalak and White, 2010). Probability graphical models inherently model conditional independences in different ways and in addition to modelling the conditional independences some are able to represent causal relations too. The conversion from the GRiST fuzzy model to the GRiST probabilistic graphical model will involve translation of the semantics, relations and conditional independences represented by the model into appropriate probability graphs (i.e. probability building blocks) that model the same conditional independencies. During the mapping of the GRiST component structures to these building blocks it is imperative there is no loss in semantic meaning as a result of the translation process. An understanding of attributes such as causality and conditional independence at both ends of the mapping spectrum will aid in ensuring that appropriate mappings are made. Hence the need to fully explore and understand the knowledge and semantics encapsulated in the GRiST structure. The final GRiST probabilistic graphical model (i.e. the chain graph) to be used for the prediction of the risk assessments will then be constructed from the probability building blocks that the component structures map to.

The various properties of the GRiST relationship types outlined in Table 4.2, page 72 with the exception of the symmetric property are now discussed. The symmetric property is not discussed as this property does not hold for any of the GRiST relationship types (see Table 4.2). Starting with the transitivity property, from Table 4.2, it can be see that all the GRiST relations are transitive except for the *gives_details_of* relationship type. To illustrate the transitive nature of some of the relations we start with the *contributes_to* relation. Using the example of *gen-personality* (Figure 4.5), it can be seen that if *gen-controlling* ***contributes_to*** *gen-personality* and if *gen-personality* ***contributes_to*** *suicide* risk this clearly implies that *gen-controlling* ***contributes_to*** *suicide* risk. Contrast this with the *insight-resp* example (see Figure 4.6). *gen-nd-hlp-diff* (need for help with difficulties) ***gives_details_of*** *insight-resp* (insight and responsibility). Also *insight-resp* ***gives_details_of*** *suic_bhvr_const* (constraints on suicidal behaviour). However, it would be incorrect to conclude from this that *gen-nd-hlp-diff* (need for help with difficulties) ***gives_details_of*** *suic_bhvr_const* (constraints on suicidal behaviour), as the relationship type does not have a transitive property and this is also seen to be a semantically sound.

A considerable number of papers have been written on the issue of whether or not transitive relations are causal in nature; see Bonnefon et al (2008), Hesslow (1981), and Hall (2000) for some examples. Some of these are advocates of the stance that transitivity innately denotes causality, see for example Lewis (2000), whilst others have taken a more cautious approach and give several illustrations of counter examples where transitive relations are not necessarily causal. Examples of these include Hesslow (1981), Hall (2000), Hitchcock (2001) and McDermott (1995). However, there are yet others that take the stance that transitivity infers causality in some situations but not in others. Bonnefon et al (2008) illustrate causal transitivity with the following example. You want to make some tea, so you put the kettle on the fire, the water starts to boil and hence the kettle starts to whistle. The issues relating to causal transitivity that were pointed out here are 1) the water is boiling because the water has reached boiling point. 2) Would it therefore be correct to say that the kettle is whistling because the water has reached boiling point? This is seen to be correct and demonstrates $X_1 R X_2$ and $X_2 R X_3$ then $X_1 R X_3$. A counter example that depicts causal intransitivity taken from an earlier draft of Hall (2004) is that of a dislodged boulder that rolls down towards a hiker. However, the hiker sees it and ducks. The boulder hence misses the hiker and he survives the experience. The hiker ducked because of the falling boulder and would not have survived if he had not. If causal transitivity held here, we would conclude that the hiker survived because of the falling border but this does not make logical or semantic sense.

For the GRiST model, our position is based on a number of additional factors peculiar to GRiST. The factors that have to be taken into consideration, for the GRiST knowledge structure, are the types of component structures available in GRiST (discussed earlier), the constraints exhibited by these nodes, the different visualisations of these nodes (more on this will be discussed later in the chapter) and finally the Markov properties of the probabilistic graphical models that they potentially map to. However, without taking all the factors into consideration and just singly focusing on the transitive property, the GRiST viewpoint is that if a relation between variables is transitive then the relationship type may be causal. This viewpoint is similar to those which say causality can be both transitive and intransitive depending on the context and other factors. For the GRiST knowledge structure the rationale behind this stance has to do with the fact that there are instances where transitive relationships appear to be causal when considering the semantics involved. However, there are also instances where other transitive relations appear to be non-causal. When all the relevant factors are taken into consideration an even more definitive conclusion can be reached. This definitive conclusion which will be discussed further later on can be summarised as follows in the GRiST model, transitive relations default to being interpreted as causal relations. However, in some special cases (for instance if the transitive relation occurs in the context of a fixed generic component structure) other factors take precedence and the causal property is overruled.

Next we consider the reflexive and antisymmetric properties. From Table 4.2, we see that the GRiST relations that are reflexive are the *is-a* and the *part_of* relation. A *physical indicator of suicide* ***is-a*** *physical indicator of suicide.* The distinction between the allocation of the reflexity property to the *part_of* relation but not to the *component_of* relation is very subtle and as such it will be highlighted here. From the definitions of these two relations, it can be seen that the main difference between them is that for the *part_of* relation, every X_1 is at each point in time part of X_2 whereas for the *component_of* relation just some of X_1 are part of X_2 at each point in time. For the reflexive property this means that with the *part_of* relation, every element is related to itself but this is not so in the case of the *component_of* relation and hence the difference in their properties. In terms of the link with causality, the GRiST relations with the reflexive property are unlikely to be causal, as it is unlikely that an element causes itself, and as a direct logical consequence of this we would not expect the reflexive *is-a* relation to be causal. However, it should be noted that for the *part_of* relation we cannot conclusively say that it will always be non-causal but have to take into consideration the other causality determining factors (this will be expanded on during the development of the mapping rules). This relation property is an example of one in which Hill's Temporality criterion also comes into play.

The final relation property to be considered is the antisymmetric property. Considering the GRiST relations if X_1 *is-a* X_2 and X_2 *is-a* X_1, it makes logical sense to conclude that X_1 and X_2 must therefore be the same. In a similar vein, if X_1 *part_of* X_2 and X_2 *part_of* X_1, if we think in terms of subsets of a set, then if X_1 and X_2 overlap in such a way that their elements fully overlap, then they will be equal and the antisymmetric property will hold (this means that it can hold but not necessarily always so). If on the other hand we consider the *component_of* relation, this is closer to the notion of a perfect subset where the elements of the sets will never fully overlap and hence the antisymmetric property does not hold. For the above reason, again like the reflexive property when it comes to causality, we need to consider the other relevant factors. However, unlike the reflexive property, relations with a potential to be antisymmetric can only be causal if the antisymmetric property does not hold in that particular circumstance (e.g. in the case of a non-fully overlapping *part_of* relation mentioned earlier).

In summary from the discussions in this section the following conclusions can be reached:

- For the two GRiST relationship types that have been identified to be reflexive, these do not map to causal relations (i.e. the *is_a* and *part_of* relations). It is also interesting to note that these are the relationship types that are usually used to represent set or class memberships and in keeping with the current conclusions these do not generally map to causal relations. Also it can be seen that for the relations that have the reflexive property even though they have other properties (e.g. transitivity) the reflexive property takes precedence over the other properties.

- For the relationship types that are transitive (and not reflexive), the default behaviour is to map to being causal. However, when all the influencing factors are taken into consideration (such as the context within which the relation is defined, is it within a fixed generic component and so on) then it is possible that the causal nature will be overridden. However, generally the default behaviour is that it is causal (these additional factors and the order of precedence will be discussed in more detail in Chapter 5).

- For the antisymmetric relations the default characteristic trait is non-causality.

4.3 Formal Coding of the GRiST Relationship Types

Although the process of defining the relationship types between the various nodes in the GRiST knowledge structure contains a subjective element, nevertheless it is still important to have a formal coding method for the process.

The process involves identifying the various relationship types between the nodes and labelling each link as one of the identified types (i.e. *is_a*, *gives_details_of*, *precedes*, *contributes_to, part_of,* and *component_of*). The first relationship type to be checked for is the *is-a* relationship type. This is simply because it is the easiest to both define and identify.

We consider the question: Are nodes X, Y types of node Z? An actual example from the GRiST knowledge structure is *degree of aggression/hostility* and *how upbeat or downbeat/depressed* which have an *is-a* relationship with *general risk tone*, simply because they are types of tones (i.e. being aggressive or upbeat). A second example is the nodes *alcohol misuse* and *drug misuse*, which are both types of *substance misuse*.

After these have been identified the next type of relationship type to be identified is the *gives_details_of* relationship type. Nodes that the *is-a* relationship type have been identified between, need not be reconsidered. It will be unnecessary and time consuming to re-scan through and process the entire model again (and redundant). By definition the *gives_details_of* relationship type exists between nodes where further details of one of the nodes is given by the other node and its siblings. An example of this is seen in the nodes *first time suicide attempt occurred*, *how many suicide attempts* and *suicide attempts escalating in frequency* all of which give further details of the *pattern of suicide attempts* concept node. In this relationship type, there is a clear correlation (correlation is used here in a non-mathematical sense) between the nodes, in the example used they are all related to the pattern of suicide attempts.

The next relationship type to be identified is the *contribute_to* relationship type. This relationship type differs from the previous one, in that the relationship generally depicts a causal relationship i.e. if node X has a *contribute_to* relationship with node Y, this means that node X directly influences and contributes to node Y. Examples of this relationship type from the GRiST knowledge structure are, the nodes *insight and responsibility* and *religious values/beliefs affecting suicide risk,* these two variables have a causal relation to a person's *constraints in suicidal behaviour*. Another example is the influence that the sibling nodes *feelings and emotions*, *person's perspective of self worth*, *voice hallucinations*, *general motivation in life*, *paranoid delusions*, *impaired cognitive function*, *general current behaviour*, *person's behavioural presentation* and *engagement with world* have on the variable *serious depression.*

The *preceding* relationship type is then identified within the model. An example from the GRiST knowledge structure is the relationship between *past suicide attempt* and *suicide risk*. Finally the last two relationship types are then also identified; the *part_of* and *component_of* relation, the difference between these two appears to be slight. However, it is important to distinguish between them because it affects how they are mapped to probability building blocks, from the earlier discussion on their differences it was seen that the *part_of* relations does not generally exhibit causality whereas the *component_of* relations can. The *component_of* relation depicts a relationship type where internal nodes and their siblings together constitute a root node.

In summary to map the relationship types between the various nodes in the GRiST knowledge structure, we start with the *is-a* relationship type, followed by the *gives_details_of, contribute_to*, *precedes, part_of* and the *component_of* relationship types.

4.4 Extending the GRiST Knowledge Structure into Concept Maps

Once the various relationship types were identified, the concept maps for the GRiST knowledge structures could then be constructed. A concept map allows one to represent the knowledge structure of a domain in an easily accessible manner. To reiterate, the idea behind the use of concept maps is to extend the current GRiST knowledge structure by the addition of relationship types between the concepts within the GRiST knowledge structure.

An example of a subsection of the GRiST concept map can be seen in Figure 4.3, in this figure the focus is on *motive-eng* and *gen-personality* and so only these concepts and their internal nodes have fully labelled relationship types in Figure 4.3. This concept map was produced using CMapTools knowledge modelling kit (Cmap Tools, n.d.). A one to one mapping exists between the GRiST knowledge structure nodes (i.e. concept and datum nodes) and the nodes represented in the concept maps.

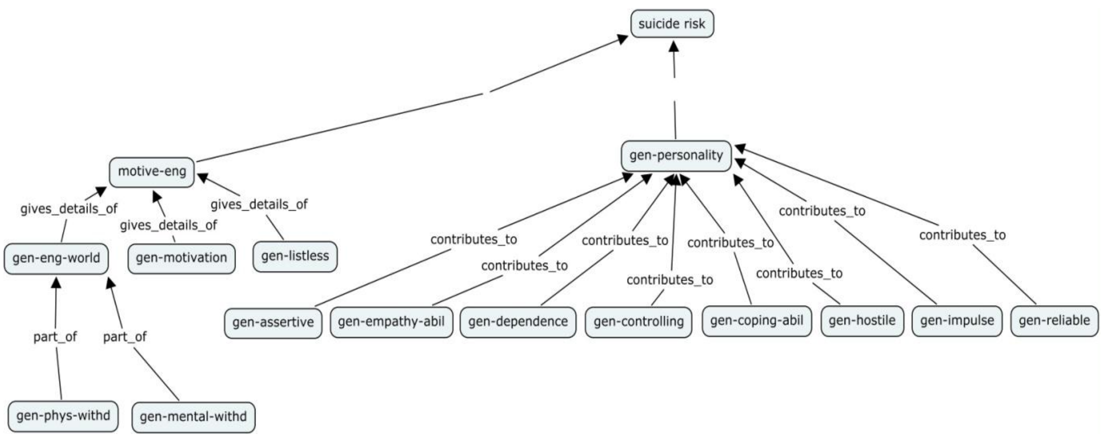


Figure 4.3: Subsection of GRiST suicide concept map.

Figure 4.3 and various other figures in this thesis use the GRiST knowledge structure code names to describe the nodes within the structure. Appendix 1 contains a full listing of all the code names in the Suicide section of the GRiST knowledge structure and their corresponding labels. The code names are simply short descriptions of the various nodes, whilst the labels are more meaningful descriptive names for the corresponding nodes. Table 4.3 gives a snapshot of the listings in Appendix 1 that relate to the nodes in Figure 4.3.

Table 4.3: GRiST knowledge structure code names and descriptions

Node Code Name	**Description**
motive-eng	motivation and engagement with world
gen-eng-world	engagement with world
gen-motivation	general motivation in life
gen-listless	listless, no energy, slowed down, loss of drives
gen-phys-withd	physical withdrawal from world
gen-mental-withd	mental withdrawal
gen-personality	personality
gen-assertive	assertiveness
gen-empathy-abil	ability to empathise
gen-dependence	dependence
gen-controlling	controlling/organisational approach
gen-coping-abil	capacity to cope with major life stresses
gen-hostile	Hostility
gen-impulse	impulsiveness
gen-reliable	Reliability

4.5 Representation of GRiST Ontology in OWL

The next stage in the ontology development process was to explore briefly a possible representation of the GRiST concept map in an ontology language. This process was carried out for the same reason as the earlier exploration of the relationship types, to distinguish the types of concepts that help determine the most appropriate probability structure for conversion. This ontological representation provides a formal underpinning to the GRiST XML structure, where required concept maps produced using the CMapTools served as a starting point for ontology development using OWL (W3C, n.d.) and this was utilised in the examination of the potential GRiST ontology.

The OWL ontology language was chosen, simply because of its universal use and acceptance across a wide spectrum of domains. Next a possible GRiST ontology using the OWL language is discussed. It represents a small snapshot of a possible method of developing a GRiST ontology bearing in mind the objective of identifying the best structures from GRiST for mapping to appropriate probability building blocks. However, prior to the ontology development discussion we briefly revisit some of the past work done on ontologies in the mental health domain and how they relate to GRiST.

An ontology provides a way of representing and sharing knowledge about a domain, in a formal structured way. A large amount of research has been done on the development of ontologies. However, in mental health ontologies possibly as a result of the complexity and vastness of the mental health domain, the various ontologies seem to focus on different aspects of mental health and none completely subsumes the others. The GRiST knowledge structure was developed focusing on a wide range of mental health issues (such as suicide, harm to others, self-harm and so on) and the particular knowledge elicitation task given to the domain experts involved in the development of the model, was to identify the risk factors for the various mental health risk areas and how they impact on each other. With some of the other knowledge structures the emphasis of the collected knowledge is different from that of GRiST. For example in DecisionBase which is said to be the most professional available program for psychiatric diagnosis (DecisionBase n.d.; Haghighi et al, 2009) the emphasis is on diagnosing mental illness. In some other ontologies priority is given to the defining of the various relationships that exist between the diseases and treatments, whereas as mentioned earlier in GRiST the emphasis is on the risk factors that lead to potential mental health risks (such as suicide, harm to others and so on).

4.5.1 OWL Classes in the Ontology

In OWL, classes represent sets that hold domain objects within them. Representing the GRiST knowledge structure in a model represented by classes is not a straightforward task. This is because of both the nature of knowledge represented in the GRiST structure and the way the knowledge is structured and arranged. When classes are organised into a super class/subclass form, this generally represents a generalisation/specialisation relationship and parts of the GRiST knowledge structure can in fact fall into this kind of category. For example *general drug misuse* and *general alcohol misuse* are clearly specialisations of *general substance abuse*. However, there are many relationships within the GRiST knowledge structure where the correct link type between the nodes are parent to child but cannot be defined as a generalisation/specialisation relationship. For example in Figure 4.6, *suic-first-occ*, *suic-how-many* and *suic-escalate* are not specialisations of *suic-patt-att* (i.e. the pattern of the suicide attempt). This leads to the need for a variant where appropriate relationships are defined via class relationships and others purely through the relationship type that they share. In our example from Figure 4.3, *suic-first-occ*, *suic-how-many* and *suic-escalate* simply give further details of the pattern of the suicide attempt. Many other examples where the relationship that exists needs to be the overriding factor can be seen throughout the entire GRiST knowledge structure. If the assumption was made that the relationship between every two nodes in the GRiST knowledge structure that are directly linked together is one of super class to subclass (see Figure 4.4 for a depiction of this using OWL), although this will be easy to model using OWL, it will be flawed and an incorrect representation of the semantics contained within the GRiST knowledge structure. The conclusion that was hence reached was that in order to accurately model the GRiST knowledge structure using OWL, an alternative method to the classes approach must be sought and used. In the next section the alternate approach is discussed, this is representation of the GRiST knowledge structure via the use of OWL properties which will be shown to facilitate the modelling and defining of the relationships between the GRiST nodes.

4.5.2 The Phases of the GRiST Ontology Development

As described earlier from the GRiST knowledge structure, the concept map which depicts the relationships that exist between the various nodes is specified, the next stage after this is then the development of the mapping rules from the constraints and relationship types contained within the GRiST ontology. This will in turn lead to the mapping to probability building blocks, which will then culminate in the development of the final chain graph. Here we describe briefly the processing that needs to be done to the concept map prior to the ontology development. We then again briefly discuss the ontology modelling processing and end this subsection on the GRiST ontology by exploring the decomposition of the ontology into component structures, to be mapped to probability building blocks and the resultant chain graph.

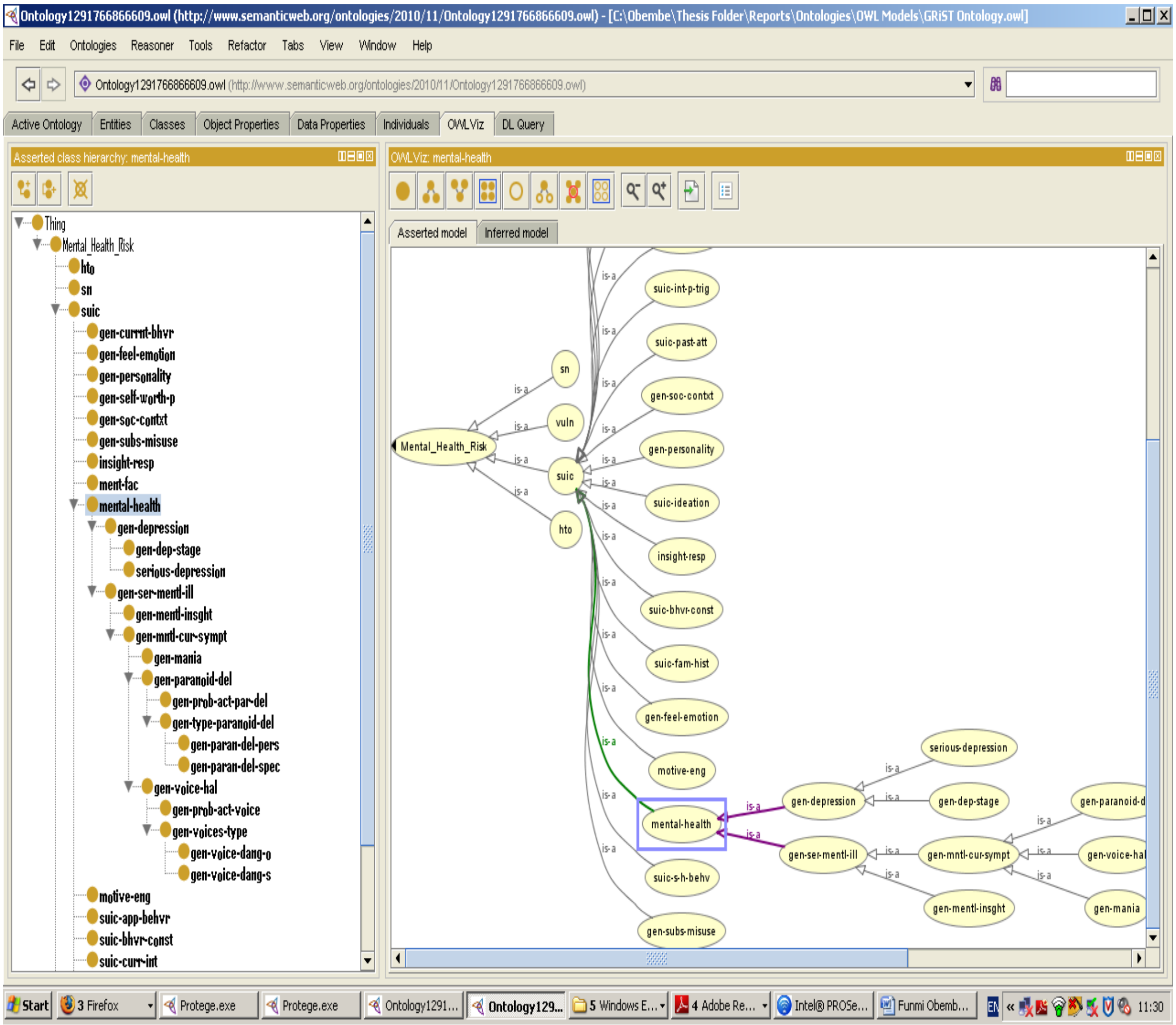


Figure 4.4: Subsection of GRiST ontology modelled as having superclass to subclass throughout the domain.

4.5.3 Pre-Ontology Modelling Processing

In the GRiST knowledge structure apart from classifying nodes into either datum nodes or concept nodes, we can further categorise them into non-generic, generic distinct or fixed generic nodes (see Chapter 2). Prior to the ontology modelling, the GRiST knowledge structure is broken down into these groups using the following rules:

- The GRiST knowledge structure is scanned from the bottom of the hierarchy (i.e. the datum nodes end of the taxonomy). This is done in the first instance in a bid to identify all the generic component structures (i.e. both their root nodes and internal nodes). For both fixed generic and generic distinct component structures, the root node is identified by scanning up the hierarchy in the direction of the top risk, all the fixed generic and generic distinct nodes that are scanned are classed as internal nodes of a root node. The root node is reached once the scanning results in the last generic node that is not the top risk node.

- The type of the component structure is dependent on the root node i.e. if the root node is a fixed generic node then the component structure is fixed generic and in a similar vein if the root node is generic distinct then the component structure is generic distinct.
- Examples of this can be seen in Figure 4.5, where scanning from the bottom of the hierarchy from the datum node *gen-cog-think-mem,* when we scan up to the *ment-fac* node we would have reached a non-generic node and so moving down the hierarchy by one step, *gen-impaird-cog* is the last generic node to be reached and is therefore the root risk. Its internal nodes are *gen-cog-think-mem* and *gen-concentr.*
- After all the fixed generic and generic distinct component structures have been identified, the ontology pre-processing is complete and we can now proceed with the modelling of the ontology.

4.5.4 Exploring the GRiST Ontology Model

In the GRiST ontology representation in OWL, the choice was made to model the ontology as a physical model with each node in the GRiST knowledge structure represented in the ontology. For possible alternate design choices, such as the representation of concept relationships as parent-child (the class to subclass view), see Wrighton and Buckingham (2009). The rationale behind our choice is that unlike in traditional ontology developments, where the main objective of the ontology is to represent a particular domain (i.e. the concepts and relationships between them) to aid sharing of information, our main aim is to explore the links (relations) between the concepts in the GRiST model and how these and equivalent links have been (and would be) represented using an ontology language such as OWL.

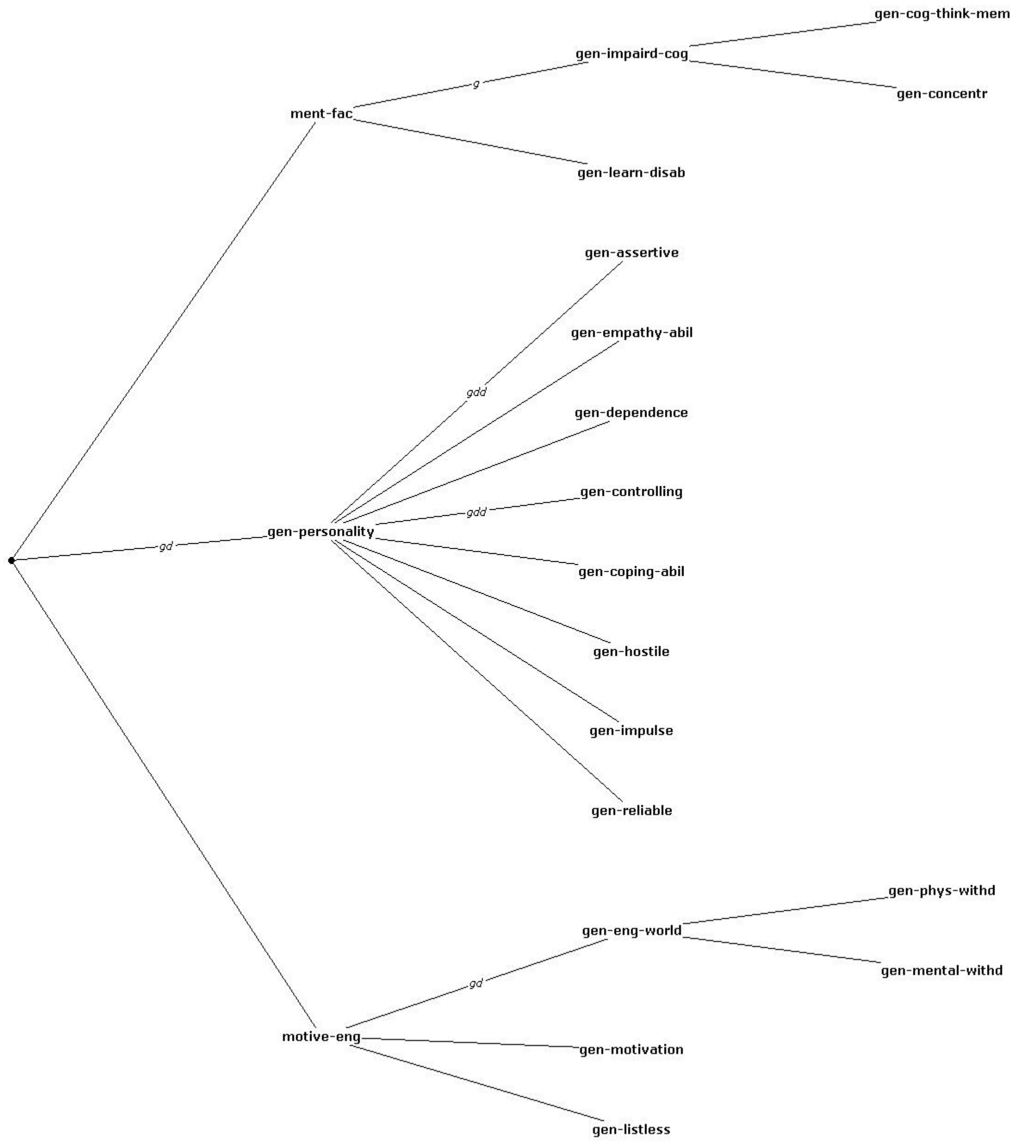


Figure 4.5: Subsection of GRiST knowledge structure I (‘*g’ and ‘gd’* denote ‘FG’ and ‘GD’ components respectively; whist *‘gdat’* and ‘*gdd*’ are the respective datum node equivalents).

The purpose of this OWL ontology is to aid the analyses of the GRiST knowledge structure leading to the identification of the correct probabilistic equivalents; recall that the ultimate aim is the mapping from the GRiST knowledge structure to a probabilistic graphical model. Next the modelling of relationship types that are not of the form super class to subclass using OWL is examined.

4.5.5 GRiST General OWL Classes

In the GRiST OWL ontology, three general classes are modelled, namely the non-generic class, the fixed generic class and the generic distinct class. The various component structures that the GRiST knowledge structure decomposes into are then categorised in the ontology as being members of the relevant classes. For example from Figure 4.5 the fixed generic component structure with root node *gen-impaird-cog* (impaired cognitive function) is a member of the OWL fixed generic GRiST class, the component structure with root node *gen-personality* (personality) is a member of the class generic distinct and the node *motive-eng* (motivation and engagement with world) is a member of the non-generic OWL class.

The general properties held by each of these class types are added to the OWL definitions for each of them. The advantage of modelling these three general classes in OWL is that every node or component structure that is a subclass of any of the classes automatically inherits the properties of the said class. Below we summarise the properties and outline the modelling of these using OWL.

- Members of the non-generic class must have their cardinality fixed to one. Here cardinality refers to the magnitude of the relation between nodes. That is, the members of this class share a one to one relation.
- Members of the fixed generic class can occur in more than one location in the model and always have both the same structure and the same uncertainty values.
- Members of the generic distinct class can occur in more than one locale but differ from the fixed generic class in that even though they always have the same structure, their uncertainty value varies depending on the context (i.e. their location in the model). However, as the initial model does not include uncertainty, we do not initially see any distinction between the generic-distinct and the fixed generic classes but when the extension of the ontology to include the uncertainty representation that is encapsulated in the GRiST fuzzy model is briefly explored in section 4.6, the difference between the two classes can be seen.

As mentioned earlier, since each structure that belongs to any of these classes inherits its defined properties, if a structure violates any of its class properties, the reasoning facility in OWL will flag it up as an error. So a non-generic class structure cannot be modelled in multiple locations and be seen as valid, this will generate an error because by definition one of the properties of the non-generic class is that it can only occur once in the model.

To model this in OWL, we exploit the fact that the underlying knowledge representation paradigm that exists in OWL is description logics (Nardi and Brachman, 2010). One way to explore a possible method for the development of a GRiST ontology from the GRiST knowledge structure is by considering the possible description logics that can be used to describe and model the GRiST knowledge structure. The descriptive logic that we use to capture the properties of each of this classes result in axioms that provide the constraints that ensure that the properties of the classes are well defined.

To start off, the generic distinct and fixed generic structures that were identified during the pre-ontology processing were assigned to the appropriate OWL generic-distinct or fixed generic class. Below is an example of part of the process of defining the various non super class to subclass relationships in the ontology. With reference to Figure 4.6, some of the relationships between the nodes can be written out as follows:

i. suic-first-occ *gives_details_of* suic-patt-att
ii. suic-how-many *gives_details_of* suic-patt-att
iii. suic-escalate *gives_details_of* suic-patt-att
iv. suic-patt-att *gives_details_of* suic-occur
v. suic-most-rec *gives_details_of* suic-occur
vi. suic-past-att *contributes_to* suicide and so on.

We consider a simple example to illustrate how this can be modelled in OWL. As a starting point to representing one of the above statements in OWL abstract syntax, we first of all define in the syntax the non-generic, fixed generic and the generic distinct classes (see Grimm et al (2007) for further details on the OWL abstract syntax and its equivalent in descriptive logic). OWL has a number of features that aid ontology development, but one that has not yet been mentioned is the notion of restrictions.

These allow concepts (i.e. classes or objects) and properties to be qualified by logical features such as ‘only’ (Kola et al, 2010). Also see Kola et al (2010) for more details on OWL features such as axioms, primitive concepts, and properties.

Figure 4.6: Subsection of GRiST suicide knowledge structure II (‘*g’ and ‘gd’* denote ‘FG’ and ‘GD’ components respectively).

Non-Generic Class: restriction (ng max cardinality(1))

Fixed Generic Class: restriction (fg min cardinality (1))

Generic Distinct Class: restriction (gd min cardinality (1))

In the above the non generic class is defined as one with a maximum cardinality of one i.e. it can only occur once in the entire model whereas both the fixed generic and generic distinct classes are defined as having minimum cardinalities of one. Minimum cardinality were used for them as against maximum cardinality because by definition there is no set upper limit as to how many times they can occur in the entire knowledge structure. And their minimum cardinality was set to one and not two, because although they can occur in more than one location in the model, it is not necessary the case.

To define the individual classes such as the *suic-first-occ* (suicide first occurrence) class, we used a combination of the different OWL features mentioned previously. The classes which represent the nodes in the GRiST knowledge structure are represented in OWL by primitive concepts, which are the basic elements that make up the knowledge structure and the class hierarchies. We then represent the relationships that exist between different primitive concepts (and that have been clearly outlined in the GRiST concept maps) using properties. So for example *suic-first-occ* will be represented by a primitive concept (i.e. a class) and will be modelled as a subclass of the non-generic class. We can also use OWL to define more complex nodes by OWL defined concepts. These are defined using a combination of primitive concepts and properties such as for GRiST generic concepts that are made up of other generic concepts (e.g. *Depression*). Together with OWL restrictions and axioms (which refer to the conditions that are assumed to be true and the constraints on the relevant objects or properties), it is possible to map the GRiST knowledge structure into an appropriate OWL ontology. For more on OWL primitive concepts, defined concepts, properties, restrictions and axioms see Kola et al (2010).

Part of the definition for the *suic-first-occ* class includes:

Class Description:suic-first-occ

Non-Generic Class

And *gives_details_of* suic-patt-att

From which we can see that the *suic-first-occ* class is a subclass of the non generic class and that it is related to the *suic-patt-att* class via the *gives_details_of* relationship type. In a similar manner the various concepts in the GRiST knowledge structure and in the GRiST concept maps can be defined and the different relationships between them defined in the ontology. Exploring the options available for this process and how this will be done, helped clarify the sub trees that the GRiST knowledge structure can be decomposed into and in two instances highlighted the need for an additional variant in the decomposition of the fixed generic and generic distinct classes. This resulted in two different kinds of component structures each for both the fixed generic and the generic distinct component structures. This will be discussed later.

After all the various concepts and their relations have been defined, we are left with two possible views in OWL. These are the asserted model and the inferred model. The asserted model is the directly modelled one whilst the inferred model is the one that is inferred from the various restrictions, axioms, properties and relationship types defined in the ontology. It is within the inferred model that we see the GRiST knowledge structure fully represented in the ontology together with the various constraints and relationship types between the different concepts. As a result of the exploration of the GRiST ontology, a number of important issues were highlighted. These include the importance of decomposing the generic structures (i.e. both the fixed generic and generic distinct structures) into the smallest possible generic structures that can occur in a location. For instance previously it was assumed that in the decomposing of the GRiST knowledge structure into the generic component structures, the most important concept was the generic concept closest to the top risk. For instance, in Figure 4.7, the root concept will be the *gen-depression* concept and together with all of its internal nodes, this would have been taken as the fixed generic component structure. However, from the GRiST ontology we see that this is only part of the solution, and it is also vital to define in their own right the generic structures that occur within the larger *gen-depression* fixed generic component structure (examples are *gen-presentation* and *gen-feel-emot*). This is important because these smaller generic components can and do occur in other contexts outside of the higher concept (in this example *gen-depression*). That is, they occur in other parts of the model where *depression* does not occur. From the ontology exploration we have therefore been able to identify the need to decompose into what we call “pure” generic component structures and component structures such as *gen-depression* that are made up of a combination of some of these smaller pure component structures. The conversion from the GRiST knowledge structure into its constituent component structures was hence done by starting at the leaf nodes and working up to the first generic concept, defining it, and then finding its context node by moving on up to the first generic fixed node or the root risk node in the path. The generic structure is then defined based on the root concept type i.e. if the root concept is fixed generic then the component structure is fixed generic and vice versa for generic distinct roots.

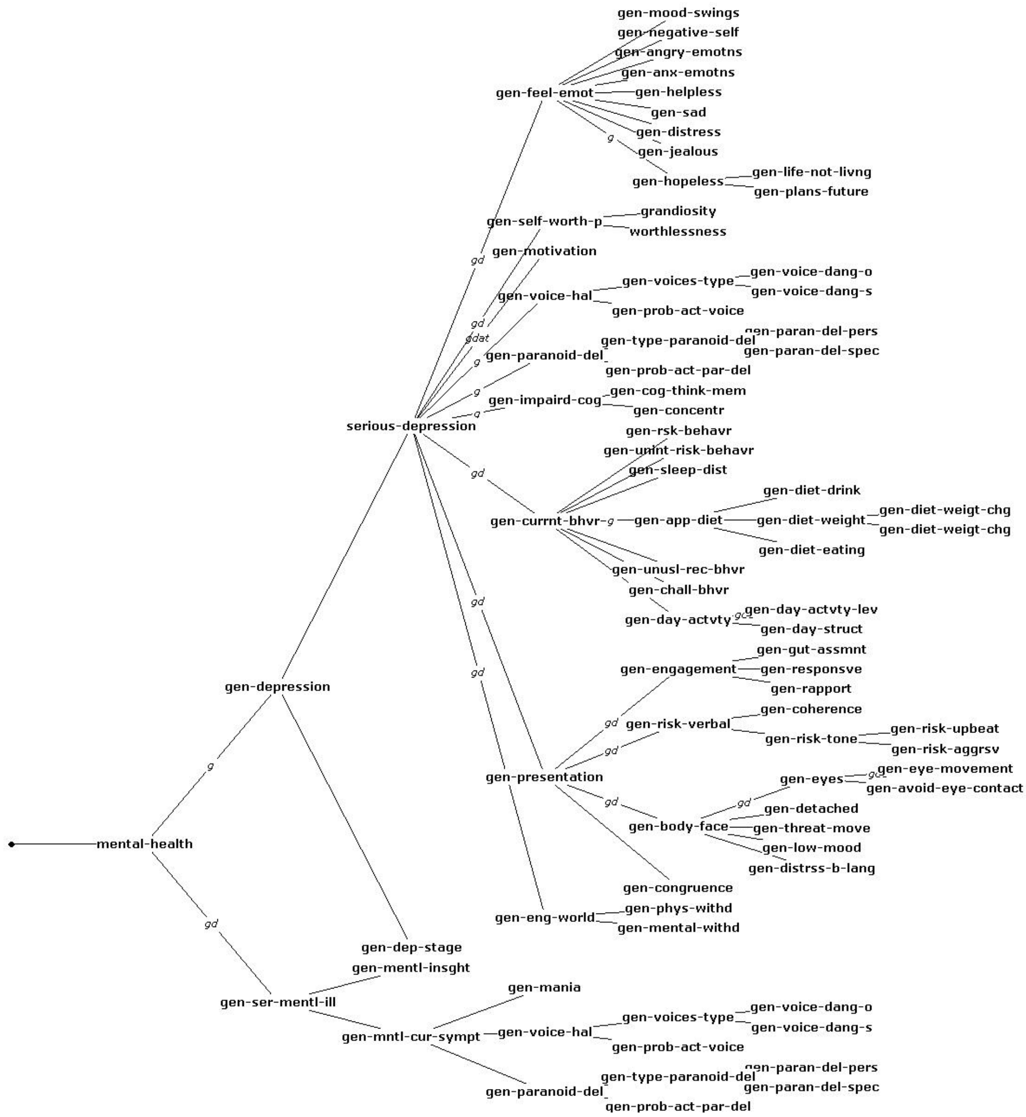


Figure 4.7: Subsection of GRiST suicide knowledge structure III (‘*g’ and ‘gd’* denote ‘FG’ and ‘GD’ components respectively).

4.6 Extending the GRiST Ontology to Handle Uncertainty

Related work has tended to look at the possibility of extending OWL to include uncertainty values (examples of these can be seen in Vacura et al, 2008 and Ding and Peng, 2004). Ding and Peng (2004) extended OWL to include uncertainty values and then converted an ontology built using this extended OWL into a Bayesian Belief Network, Fenz et al (2009) and Yang and Calmet (2005) also used similar methods.

For this research the case is different, although the OWL class system has been used to explore modelling the GRiST knowledge structure, and the notion of using its object properties functionality to add the definitions and constraints that are needed to correctly model the relationship between the various GRiST classes has been described. However, in mapping to the probability building blocks, the impact of these properties must be taken into consideration. This led to further exploration of the identified relationships between the GRiST classes, their definitions, and their semantic meanings. Careful consideration has also been given to ascertaining what information these relationship types can give about the probabilities potentially encapsulated in the GRiST knowledge structure.

In Chapter 2 on the discussion on the GRiST fuzzy model it was seen that uncertainty is represented using membership grades (MGs) and relative influences (RIs) in the GRiST model. These MG and RI values provide useful information in relation to uncertainty leading up to probability representations in the GRiST knowledge structure. From Section 2.2 it is seen that the contribution from each concept to the overall risk (e.g. suicide, harm to others and so on) is represented by the value of its membership grade and its relative influence. Hence although the precise function that relates the MG x RI value of each concept to the probability of the said concept (given the internal nodes that lead up to it) is unknown, it is clear that there is a corresponding relation between them. These are summarised for the various component types in the following equations:

- Datum Nodes

  $$MG(Datum) \propto P(Risk \mid Datum).$$

  For a datum node the membership grade of the datum node is proportional to the probability of the top risk (e.g. suicide) given the datum node. This refers specifically to the fact that the datum node's value is ultimately making some contribution towards the final probability of the top risk.

- Fixed Generic Concepts

  $$MG(Concept_{FG}) \ \alpha \ P(Concept_{FG}).$$

  For fixed generic concepts that are not context dependent the membership grade of the root concept of the component structure is proportional to the probability of the fixed generic concept. This is the case because the uncertainty values of the fixed generic component remains the same regardless of its location or context in the knowledge structure.

- Generic Distinct Concepts

  $$MG(Concept_{GD}) \ \alpha \ P(MaxRiskContribution_{Concept_{GD}}).$$

  Where $Concept_{GD}$ stands for generic distinct concept.

For the generic distinct concepts which are context dependent the membership grade of its root concept node is proportional to the probability of the maximum contribution to risk of the generic distinct concept.

- All Nodes
  $MG(Concept_{all})xRI_{path}\ \alpha\ P(Risk\,|\,Concept).$

  Finally for all nodes the product of the all their membership grades multiplied by all the RI values along their path (see Figure 2.1) is proportional to the probability of the top risk given the concept.

We extend the explored GRiST ontology by adding to the various concepts the MG and RI values as defined in the corresponding GRiST knowledge structure. These uncertainty values are then interpreted to give the following:

- For a node X that links upwards to a node Y higher up in the hierarchy, the value $MG(X)xRI_{path->y}$ gives the degree of membership of X in class Y.

The probabilistic relations that have been drawn out of the GRiST knowledge structure will play an innate part in the learning of parameters for the GRiST probabilistic graphical model from data. The learning process is discussed in more detail in Chapters 6 and 7.

4.7 Revisiting the GRiST Component Structures

As a direct result of the conclusions reached from the section on the OWL ontology representation, the GRiST component structures that the knowledge structure can be decomposed into are now extended.

4.7.1 The Non-Generic Structure

The non generic structure as mentioned earlier refers to nodes that are not generic, and as such can only occur in one location. Examples of these include *suic-occur*, *suic-first-ocurr* and *suic-ideation* from Figure 4.6.

4.7.2 The Pure Fixed Generic Component Structure

The pure fixed generic component structure refers to a fixed generic component structure, which comprises of a fixed generic root node and internal nodes that have no more than one layer of generic nodes (i.e. this component structure does not have any internal node that is itself a generic node). An example of this is the *gen-voice-hal* pure fixed generic structure (see Figure 4.7), this structure together with its internal nodes itself makes up a pure fixed generic component structure (and none of the internal nodes are themselves generic) but it is also clear that this entire structure is part of the internal structure of the non pure fixed generic structure with root node *gen-depression.* We call the component structure with root node *gen-depression* non pure because some of its internal nodes are themselves generic component structures.

It is important that we differentiate between the pure fixed generic component structures and the non pure fixed generic structures because the pure fixed generic component structures can and do occur in other locations outside of the context of the non pure fixed component structures and this same logic holds for generic distinct component structures. Another reason why it is important that we differentiate between the pure and non pure structures is that in mapping to probability building blocks it will reduce some of the complexity of the mapping process. An example of this type of component structure can be seen in Figure 4.7, where the pure fixed generic component structure with root node *gen-voice-hal* occurs both within the *gen-depression* context (see top of the figure) and outside this context (see bottom of the figure). And so we must define and model each of the pure generic component structures as structures in their own right. The fixed generic structure represents the generic root node that always has the same uncertainty values regardless of its location in the GRiST knowledge structure, the context (i.e. point of reference) for all the internal nodes is the root concept node. Within (and only within) the context of the root concept, the uncertainty values of the internal nodes are fixed and always remain the same regardless of location.

4.7.3 The Pure Generic Distinct Component Structure

The discussion on the pure generic distinct component structure is similar to that of the pure fixed generic component structure. The main difference between these two is that the uncertainty values of the generic distinct structures are context sensitive. The generic distinct structures have varying internal RIs and varying root concept MG. The context for these nodes is the top root risk node (e.g., suicide, self harm and so on). This structure has no generic ancestor or, more to the point, if it did, it behaves as an FG node and can be ignored as a GD concept. An example of the pure generic distinct component is the *presentation* concept (see Figure 4.7) which is a generic distinct component structure with root concept *gen-presentation*. Examples of the occurrence of this structure can be seen in Figure 4.7 where the root concept *gen-presentation* along with all its internal nodes are part of the non pure fixed generic component structure *gen-depression* internal nodes. However, we see the same *gen-presentation* component structure re-occurring outside of the *gen-depression* context (in the context of *suic-app-behvr* i.e. person's appearance and behaviour at assessment indicating suicide as in Figure 5.1).

4.7.4 The Non Pure Fixed Generic Component Structure

This component structure refers to fixed generic component structures that have some internal nodes that are themselves generic component structures (either fixed generic or generic distinct). An example of the non pure fixed generic component structure which can be seen in Figure 4.7 includes the component structure with root concept *gen-depression* (depression) and some of its internal nodes that are themselves generic component structures include those with root concepts *gen-currnt-bhvr* (general current behaviour), and *gen-feel-emot* (feelings and emotions).

4.7.5 The Non Pure Generic Distinct Component Structure

Again this is very similar to its fixed generic counterpart, and applies to generic distinct component structures that are made up of other generic component structures. An example is the component structure with root concept *gen-ser-mentl-ill*, which has as part of its internal nodes the fixed generic root concept *gen-voice-hal* (see Figure 4.7).

4.7.6 Operationalising the Types of Identified Subtrees

Here, we briefly summarise the types of subtrees that have been identified in the GRiST knowledge structure from the ontology exploration process. Given a GRiST knowledge structure, to categorise them into the identified component structures, the following questions and actions need to be considered:

- Are there parts of the knowledge structure that repeat in more than one context of the knowledge structure?
- Split up the knowledge structure into the sections that occur in more than one location and those that do not.
- The non-repeating nodes are the non-generic component structures.

- Next split up the sections that repeat into those that always have fixed uncertainty values and those that have varying uncertainty values depending on their context
- Repeat the last action until you have the smallest possible repeating partitions. These are the pure fixed generic and pure generic distinct component structures respectively.
- Next check the knowledge structure for larger subtrees that repeat and are themselves made up of component structures, which will give the non pure fixed generic and generic distinct component structures.

Having explored both the GRiST fuzzy model and ontology knowledge representations, the last representation type to be considered is the classes, objects and wrappers representation type, and we discuss this in the next subsection. After this, we then from all of the above develop a set of mapping rules to go from the GRiST knowledge structure to the probability building blocks. In particular we detail how they all constrain and direct the production of the mapping rules.

4.8 GRiST Decomposition into Classes, Objects and Wrappers

This is the final representation type that was examined in the GRiST knowledge structure. The elements that were identified in this representation type were categorised as classes, objects and wrappers. We will start off the section by defining the key terms used here. The terms “objects” and “classes” have been used for the semblance that they bear to their role in object oriented methodologies such as the attachment of properties to classes, and the fact that subclasses have in common at least one property of their superclass. However, other aspects like inheritance and encapsulation are neither used nor relevant in this representation type. Also, objects are not necessarily instantiations of classes in this context (they are defined and described later). The term “wrapper” on the other hand is a GRiST specific term defined specifically in this research.

- Wrapper - a convenient holder for organising concepts but with no particular semantics of its own. Examples of this include *person’s behavioural presentation during assessment*. The psychological purpose of the wrapper is to chunk units of information together so that it is easier to recall and process them but, in the case of wrappers, the chunk itself does not make a tangible concept with meaning in its own right.

- Class - a component that can hold several subclasses of the same type all of which have at least one common property. An example of this is *physical indicators of suicide* and its internal nodes.

- Object – represent nodes which have properties attached to them but they are not classes or wrappers. An object can have properties that may themselves be objects with properties. As such it is possible to have a hierarchy of objects but never an object with a class in it.

- Properties – these are a special case of an object in that they have no properties of their own. An example of properties are *suic-first-occurrence* (first occurrence of suicide) and its sibling nodes *suic-how-many* (number of suicide attempts) and *suic-escalate* (are the attempts escalating) which are all properties of *suic-patt-att* (suicide pattern of attempt). These can be seen in Figure 4.6.

In a similar fashion to the other representations, from the list of constraints produced by the representation type it is possible to infer the component structures that the knowledge structure can be decomposed into. The constraints that exist within the classes/objects/wrappers representation are as follows:

- Objects can not contain classes within them, but can have properties attached to them or have properties that are themselves objects.
- Properties have no properties of their own but simply represent the properties of the parent node that they are attached to. Properties of objects are its internal nodes, in the semantics of GRiST, and so can have RIs. However the objects differ from classes because they do not need to inherit any of these properties (i.e. internal nodes). In this representation properties map to datum nodes (i.e. the physically observable data).
- Wrappers can contain other wrappers, classes, and/or objects.
- Wrappers should not have properties of their own (i.e. they should not be directly linked to properties) because they do not represent tangible concepts.
- Classes must, by definition, be able to hold several subclasses of the same type. If a concept cannot do this (e.g. current situation), then it cannot be a class. Classes ought to have at least one common property shared amongst all its members. If not, then it is a wrapper. In other words, the objects are placed in a class precisely because they have something in common within themselves and these shared properties are the class definition. If the class cannot be defined in such a way, then it is an artificial collection i.e. a wrapper.

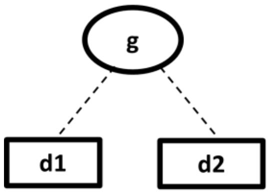
- What distinguishes a class from an object is that for all the other concepts within a class (i.e. its subclasses) there must be at least one common property held by the class. Whereas although an object can hold other objects the root object is not compelled to hold a common property. This distinguishing factor between objects and classes is significant when considering hierarchy of classes as against hierarchy of objects because it plays a part in the definition of causality and dependencies between concepts which directly affects the mapping rules between the GRiST knowledge structure and the probability building blocks.
- If a concept is not a wrapper, it must have control over its internal RIs because this makes the concept the context of its internal components. If the internal components can have different RIs in different places with the same parent, the parent is not controlling them and thus not dictating the context. Hence you can remove the parent and still have the same sense for the subcomponents. This defines the difference between an object and a wrapper.
- By definition a wrapper cannot have control over its internal nodes, because if it did, then it will not be irrelevant to the conceptual understanding of risk because it will in effect represent the context of its internal components.

Next we consider the similarities between the different visualisations and following that in Chapter 5 develop mapping rules to the probability building blocks.

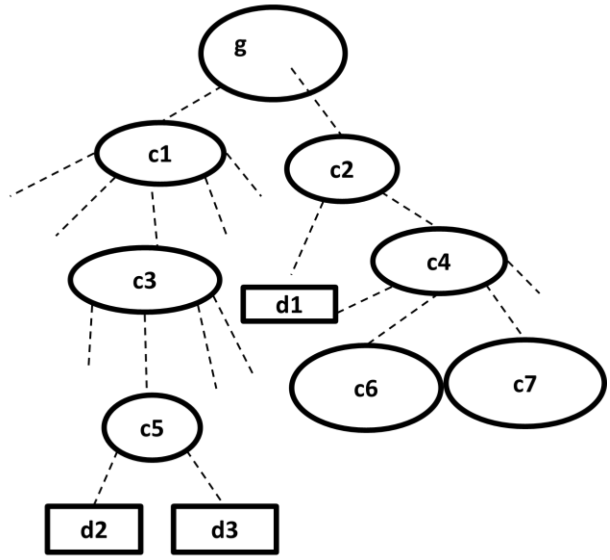
4.9 Learning from the Explored Representation Types

In this section the similarities and differences that exist between the different representation types are scrutinized and the visualisations, properties and constraints that will aid the mapping to probability building blocks are identified. For each of the parts that a comparison is done, the following headers are used:

- Fuzzy Model – This simply refers to a component structure derived from the GRiST knowledge structure of the fuzzy model (e.g. the fixed generic component structure). The sections on the fuzzy model will refer to high level and low level component structures. A low level structure is one in which none of the internal nodes are themselves generic component structures. An example from the GRiST knowledge structure is the generic distinct component structure *gen-self-worth-p* (see Figure 4.7). A high level structure is a more complex hierarchical structure, with at least one component structure as an internal node, such as the generic distinct component structure *gen-presentation* (see Figure 4.7). Figure 4.8 illustrates high and low level component structures.



(a)



(b)

Figure 4.8: Low level and high level FG structures (a) and (b) respectively. All rectangle nodes with prefixes ‘d’ in the figures refer to datum nodes whilst the oval nodes with prefixes ‘c’ refer to concepts. The two oval nodes labelled ‘g’ refer to the root FG concept node of the respective component structures.

- Ontology – This refers to any of the extended component structures derived after the OWL ontological representation (e.g. the pure generic distinct component structure).
- Classes/Objects/Wrappers – This as indicted by its name refers to any mappings to the components detailed under this representation.
- Discussion – After the mapping of the equivalent structures for each of the above representations are done, it will be followed by a discussion section which draws out rationale and conclusions arrived at from the preceding mappings.

4.9.1 First Mappings between Representations

- Fuzzy Model - Low level FG component structure.
- Ontology - Maps to pure FGs (i.e. FGs that are not themselves made up of other FGs or GDs).
- Classes/Objects/Wrappers – Objects or properties.

- Discussion – The mapping to objects makes logical sense as the root concept of the pure FG has control over its internal RIs, and if these map to wrappers then this will not be the case. Low level FG do not map to classes and this tallies with the GRiST class semantics because by definition the class is hierarchical in nature, containing other classes and at least one property that is common to its subclasses whilst the low level FG is non-hierarchical. The observed mapping to properties also tallies with the fuzzy model, as datum nodes which map to properties can be of the type FG. Examples from the GRiST knowledge structure include *gen-impaird-cog* (impaired cognitive function) and its internal nodes (see Figure 4.5) which in the classes/objects/properties visualisation maps to an object.

4.9.2 Second Mappings between Representations

- Fuzzy Model - High level FG component structure.
- Ontology – Maps to non pure FGs.
- Classes/Objects/Wrappers – Objects or classes
- Discussion - Same as above with regards to objects and classes, examples from the GRiST knowledge structure include *depression* and its internal nodes (see Figure 4.7), which in the third visualisation maps to an object. However, unlike their low level counterparts, they cannot map to properties, this is because any high-level structure cannot be a property because by definition properties cannot be hierarchical.

4.9.3 Third Mappings between Representations

- Fuzzy Model - Low level GD structures.
- Ontology – Maps to pure GD structures.
- Classes/Objects/Wrappers – Wrappers, objects or properties.
- Discussion - The pure GD structures map to wrappers, objects or properties. The observed mappings to wrappers make logical sense when we recall that wrappers are just convenient containers with no particular semantics of their own. Also as the removal of the wrapper would not make any difference to the conceptual

understanding of risk, therefore the mapping from the pure GD structures, whose root concepts have no control over their internal nodes makes logical sense. However, having observed the above, we also observe that GD structures can also additionally map to objects or properties. The mapping to properties might seem easier to rationalise than the mapping to objects. However, the logic behind this is that as the structure is a low level GD structure, everywhere it maps to an object, this structure is contained within a “larger” FG or GD structure (i.e. high level) and hence within the context of the high level root component. In such situations, even if the low level GD structure maps to an object ultimately the behaviour of its RIs are determined by the root node of the higher level structure within which it resides and if this is an FG root concept then the behaviour of the object remains consistent with expected results. An example from the GRiST knowledge structure where a pure GD structure maps to an object is *gen-eyes* (eyes), which has as internal nodes the two properties *gen-avoid-eye-contact* (avoiding eye contact) and *gen-eye-movement* (eye movement). The FG root node that applies to this object is *depression* (see Figure 4.7).

4.9.4 Fourth Mappings between Representations

- Fuzzy Model - High level GD structures.
- Ontology – Maps to non pure GD structures.
- Classes/Objects/Wrappers – Wrappers.
- Discussion - Again in this category the discussion on these mappings is the same as the above (i.e. low level GD structures) for the mappings to wrappers. However, they cannot map to properties, as by definition properties cannot be hierarchical. Furthermore it also differs from its low level counterpart in that high level GD nodes like *gen-presentation* (persons behavioural presentation during assessment) do not map to objects. These concept maps to wrappers. Another example is the *gen-ser-mentl-ill* (serious mental illness) concept which also maps to a wrapper.

4.9.5 Fifth Mappings between Representations

- Fuzzy Model - Non Generic structures.

- Ontology – Same as in Fuzzy Model.
- Classes/Objects/Wrappers – Properties, objects, classes or wrappers.
- Discussion – The observed mapping here highlights the fact that as non generic structures occurs only once in the model, a lot of the peculiarities seen in the generic structures (of both FG and GD variants) are not relevant to it. Examples of this from the GRiST knowledge structure include *suic-past-att* (past and current suicide attempts) which map to an object and the *suic-prep-serious-at* (preparation and seriousness of suicide attempts) which map to a property. Other examples from GRiST (see Figure 4.6) include *physical indicators of suicide* which maps to a class, *suic-curr-int* (current intention to commit suicide) which maps to an object and *suic-person-per (person's current perspective on suicide attempts)* which maps to a property.

4.9.6 The Different Visualisations and Relationship Types

From the last section on the similarities between the different visualisations of the GRiST knowledge structure considered in this chapter the following summarises some of the conclusions reached. The rationale behind the identification of either causality or non-causality is to aid the mapping to appropriate probability blocks. For example a structure whose relations are causal in nature can more naturally be represented by a directed graph than an undirected graph. Some of the identified associations between the representations examined and the relations between nodes are as follows:

- For low level FG component structures that map to objects or properties, the relationship types between these nodes generally tend to be non causal. An example is the low level FG object *gen-impaird-cog* (impaired cognitive function) concept and its sibling node *gen-learn-disab* (learning disabilities) which both share a non causal *gives_details_of* relationship with the *ment-fac* (mental faculties/cognitive capacity) concept.
- For high level FG component structures that map to classes or objects such as *depression,* it was observed that the dominant relationship types between their nodes tend to be non causal. However in some instances exceptions to this can occur. Figure 4.7 contains an example in the form of the high level FG *depression* with internal nodes *grandiosity* and *worthlessness* which contribute to *gen-self-worth-p* (general perspectives of self worth) and share a causal relation

contributes_to between each other. In Chapter 5 where the mapping rules are developed, the rules to determine which attribute takes precedence are outlined.

- For low level GD component structures that map to objects or properties it was observed that both causal and non causal relations exist within these structures. This behaviour is stabilised by the influencing effect of a high level structure that such a low level node is contained within, this is addressed further in Chapter 5 as part of the discussion on the development of the mapping rules. An example of a low level GD that maps to an object which has non causal relations can be seen in Figure 5.1; the *gen-eyes* (eyes) concept and its properties *gen-avoid-eye-contact (*avoid eye contact) and *gen-eye-movement* (eye movement). These two properties just give more details about the state of the person's eyes and hence share the non causal *gives_details_of* relation with the object. On the other hand an example of a low level GD depicted in Figure 4.5 with causal relations is the *gen-personality* (personality) GD object with its internal nodes *gen-assertive* (assertiveness), *gen-empathy-abil* (ability to empathise), *gen-dependence* (dependence), *gen-controlling* (controlling/organisational approach), *gen-coping-abil* (capacity to cope with major life stresses), *gen-hostile* (hostility), *gen-impulse* (hostility) and *gen-reliable* (reliability). All of these internal nodes contribute to the general way that the personality comes across and hence have a *contributes_to* relationship to the root concept *gen-personality*.

- For high level GD component structures that map to wrappers, the relationship types between the GD's root node and its internal nodes generally tend to be causal. Examples of this include depicted in Figure 5.1 *gen-presentation* (person's behavioural presentation during assessment) and its internal nodes and in Figure 4.7 *gen-ser-mentl-ill* (serious mental illness) and its internal nodes. The implication of this when it comes to mapping to probabilistic building blocks is discussed in Chapter 5.

In the next chapter (i.e. Chapter 5), the different aspects of the GRiST knowledge structure that have been discussed in the current chapter are built upon to develop a set of mapping rules that can most accurately represent the GRiST knowledge structure.

4.10 Conclusion

In this chapter the deconstruction of the fuzzy GRiST knowledge into formal substructures that guide the mapping into probability structures has been explored. The similarities and differences between the various visualisations and some of the implications that these can have for the mapping to the probability building blocks were also considered. The ultimate objective of the chapter was to ensure that the structure of the GRiST fuzzy model was fully explored prior to the development of mapping rules to the probabilistic graphical models. This objective was achieved via the following

- The exploration of the hierarchical tree structure of the GRiST fuzzy model.
- Exploration from the GRiST ontology angle, where the focus was on the types of concepts and datum nodes (e.g. generic or non-generic) and the type of relationships that exists between them and the properties of these relations.
- The final approach was the classification into classes, objects and wrappers. The GRiST knowledge structure was shown to naturally decompose into these categories.

In the next chapter (Chapter 5) all the various aspects explored in this chapter are brought together and used to develop the mapping rules required to translate between the GRiST component structures and probability building blocks. The process of combining the identified probability building blocks will eventually result in the GRiST chain graph which will be used for the assessment of the mental health risk. The discussion on this process is continued in Chapter 5.

Chapter Five

5. The Mapping Rules

In this chapter we discuss the development of the mapping rules which govern the translation process for the conversion of the GRiST knowledge structure into the final GRiST chain graph.

This chapter directly builds on preceding chapters that have examined the GRiST component structures, relations between GRiST nodes, the various representations of the GRiST knowledge structure and the probability building blocks (i.e. Chapters 2, 3 and 4). The content covered in this chapter can be broadly split into two parts. In the first half, the different aspects of the GRiST knowledge structure examined up to this point are brought together in a bid to determine what information they individually give about the properties represented in the GRiST knowledge structure. These properties mainly include causality, conditional independence and dependency. Following on from this, an examination is done to determine what information regarding causality and the like can be obtained from the various combinations of these properties (e.g. a wrapper with *is-a* relationship links). At the end of the first part the objective is to have a clear and concise list of the possible combinations of the various properties and what can be inferred from them in particular in relation to causality and conditional independence and dependencies.

In the second half of the chapter, the first half is expanded on by mapping the different representations and their meanings in terms of causality and independence (and dependency) that were identified in the first half to probability building blocks. This will draw on areas covered in Chapter 3, where the Markov properties of the different probability graphs and what they mean in terms of conditional independence and causality was covered. The general idea here will then be to map the combinations identified in the first half of the chapter to the appropriate graph with the Markov property that accurately represents each one. Having completed the above, the mapping rules are then formalised by putting together a concise list of the mapping rules for the different possible combinations. The chapter then concludes with a full explanation of how GRiST maps to a chain graph.

5.1 The GRiST Relations

From the general semantics of the relations that can exist between the GRiST knowledge structure nodes, using a general (default based) approach (as against an "every situation is covered" approach) the following were inferred:

- The *gives_details_of* relation is generally non causal. This can be seen from the definition of the relation and its semantics. An object that describes another object is a property and not a catalyst of any kind of change in the object. If we recall from Hill's Biological Influence criterion (see section 4.2.2) the greater the value of the causal element the greater the observed effect, this kind of effect will not be seen between variables linked via the *gives_details_of* relation.
- The *is_a* relation can have a variety of meanings with subtle differences depending on the variables being modelled (Brachman, 1983). Some of these meanings include a class relationship, generalisation/specialisation relationship, and so on. In the GRiST knowledge structure the definition of the is_a relation is that of "a kind of" definition. This implies that for two variables where X_1 *is_a* X_2 then X_1 is a type of X_2 and not a causal factor for it. This therefore leads to the conclusion that the *is_a* relations like the *gives_details_of* relation is generally non causal.
- The *contributes_to* relation represents the case where the internal nodes contribute to and causally influence the parent node. An example of this can be seen in Figure 4.6 for the parent node *suic-bhvr-const* (constraints on suicidal behaviour) and its children nodes *insight-resp* (insight and responsibility) and *suic-rel-belief (*religious values/beliefs affecting suicide risk). In this type of relationship the internal nodes have a direct influence on the parent node. For instance a person's religious beliefs on suicide and their insight and responsibility will directly affect the constraints that they have when it comes to suicidal behaviour. The properties of the relation also support the case for it being causal, as it is transitive and not antisymmetric.
- The *part_of* relation is generally non causal as for a variable X_1 to cause another X_2 , X_1 needs to not only fulfil certain criteria (e.g. Hill's Criteria for Causality) but X_1 needs to be a separate and distinct variable from X_2. From the definition and semantics of the *part_of* relation, it is evident that this is not the case here.
- The *component_of* relation in most instances is non causal, and the rationale behind its lack of causality is similar to that of the *part_of* relation. However in some cases, it can potentially be causal.

- The *precedes* relation is an interesting one, in that it can either be causal or non causal. The characteristic trait that it exhibits will depend on other relevant factors and the specific context in question.

5.2 The GRiST Visualisations

From the different visualisations the following were determined:

- High level GD component structures generally map to wrappers, and they tend to have causal relations between them.
- Low level GD component structures map to objects or wrappers and were seen to exhibit either causal or non causal relations (dependent on other criteria).
- High level FG component structures map to either classes or objects and generally tend to have non causal relations. However there are some examples of instances where some high level FG component structures have non causal relations between their nodes.
- Low level FG component structures generally map to either objects or properties and tend to have non causal relations between them.

5.3 Implications of the GRiST Visualisations and Relations to Causality and Conditional Independence

In the GRiST knowledge structure and in its constituent component structures, nodes that are related to each other are linked. In Chapter 4 the different possible relations were examined in-depth. Hence it can be inferred that nodes that do not share a link either directly or indirectly are not related to each other. Examples of nodes that are directly linked are *gen-congruence* (congruence of physical, verbal, and emotional presentation) and *gen-presentation* (person's behavioural presentation during assessment) in Figure 5.1. An example of nodes that are indirectly linked is *gen-congruence* and *suic-app-behvr* (person's appearance and behaviour at assessment indicating suicide). From the GRiST knowledge structure (again see Figure 5.1) examples of nodes that are not linked include *suic-fam-hist* (family history of suicide) and *gen-jealous* (jealousy).

Figure 5.1: Subsection of GRiST knowledge structure depicting directly and indirectly linked nodes and unlinked nodes (‘*g’ and ‘gd’* denote ‘FG’ and ‘GD’ components respectively; whist ‘gdat’ and ‘gdd’ are the respective datum node equivalents).

A pattern starts to emerge and it becomes possible to see that any two nodes that are not directly or indirectly linked can be said to be conditionally independent of each other given the other nodes in the knowledge structure.

In the previous section and also in Chapter 4, in examining the GRiST visualisations and the relationship types that they tend to have between their nodes, for some of them (such as the low level GD and the high level FG) it was seen that it was possible for these to have no particular kind of relation as their default type (i.e. they could equally have either causal or non causal relations). A clear example of this is in the case of the low level GD.

We now examine the implications of this for the process of developing the mapping rules. To help motivate the discussion, the definition of the different types of links that a component structure can have is illustrated in Figure 5.2, for each structure in the mapping to probability building blocks there are two distinct link types to consider; 1) what we term the internal links, which refers to the type of links between the internal nodes of the structure and 2) the external link type, which refers to the type of link between the root node of the structure and other neighbouring nodes or structures external to the structure being considered (see Figure 5.2).

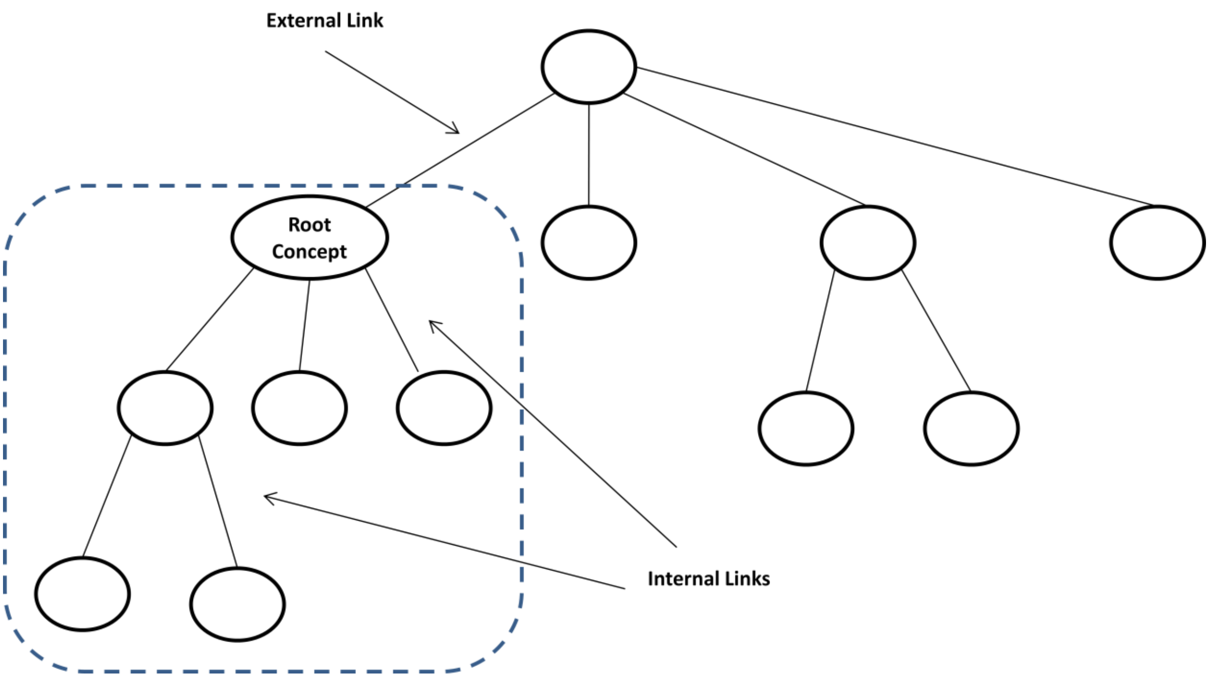


Figure 5.2: Figure depicting a component structure's internal and external links.

A low level component structure such as *gen-eyes* and its internal nodes *gen-avoid-eye-contact* and *gen-eye-movement* of Figure 5.1 will by definition be contained within a 'larger' high level generic component structure. In the example in Figure 5.1 cited (i.e. *gen-eyes)* the high level component structure it is contained within is the GD component structure *gen-presentation*. It is this high level's component root node that will determine the behaviour exhibited by the low level GD component structure. This overrides the relationship type defined between the low level component structures nodes. For example if a GD low level component structure that has causal relations is contained within a high level FG component structure which generally is non-causal, then this non-causal behaviour of the high level FG component structure overrides the causal characteristic of the low level GD structure and it is modelled as part of the non causal high level FG structure. This is important in the mapping to the probability building blocks and helps to ensure correctness and consistency in the conversion process. A similar thing applies for low level FG component structures too, as they too are contained within a high level component structure whose root node becomes the context for the low level FG component structure and hence determines its characteristic traits.

This thus leads to the conclusion that the external links between low level FG structures are dependent on the higher (in terms of the tree structure hierarchy) root node to which the low level FG structure is an internal node i.e. whether this "higher" root node is an FG or a GD structure will determine the link types between the low level FG structure. The same is also true for the external link type of low level GD structures. An additional example from the GRiST knowledge structure will be used to illustrate this and how it impacts on the mapping rule from the low level FG structures to the probability building blocks. Our example low level FG structure from Figure 4.5 is the *gen-impaird-cog* (general impaired cognitive) concept which has two internal nodes, *gen-cog-think-mem* (general cognitive thinking processes and memory) and the *gen-concentr* (general concentration) node. Focusing on the *general impaired cognitive* concept within the context of the GRiST knowledge structure, as an FG structure its uncertainty values remain the same regardless of its location, which implies that it is conditionally independent of the top risk (in this case *suicide*) and its neighbouring nodes given the FG component's root risk (i.e. the *general impaired cognitive* concept) and its internal nodes (i.e. the *cognitive thinking processes and memory* and the *general concentration* nodes).

5.4 Linking the GRiST Properties and the Probability Building Blocks' Markov Properties

Probabilistic graphical models and their properties were discussed in Chapter 3. In this section, links between the GRiST component structures and the Markov properties of the graphical models are described. This serves as a further stage in the process of developing the mapping rules from the GRiST component structures to the probability building blocks. The first probability graph whose Markov property is to be considered is that of the Markov random fields, which are undirected graphs.

5.4.1 Mapping to Markov Random Fields

For the subsequent discussion we use the same definitions of Markov properties given in section 3.3.1 page 54. Considering the pairwise and local Markov properties, these can be related to the GRiST FG component structures as follows. In the discussion on the constraints of the FG component structure (Chapter 2), it was seen that the FG component structure is context independent and the context of all its internal nodes are characterised by its root concept only and not the top risk. This directly maps to the concept of the pairwise and local Markov properties and implies that the FG root concept node is independent of other variables given its internal nodes (which are in essence its neighbours). This directly correlates with the notion of the FG structure being context independent. Furthermore it can also be seen that high level FG internal links map to Markov random fields because their contribution to the risk is always the same regardless of their location or the neighbouring nodes around them. If they are mapped to directed edges, then their semantics become constrained and to an extent determined by their neighbouring nodes and this will not be a true representation of the said nodes. Another major consideration was that in maintaining the conditional independencies represented in the original GRiST knowledge structure is whether this interpretation holds true. The only area that needs special consideration to ensure that the assertion holds true was in regards to the GD structures contained within the high level FG structure. However, what we found was that to a large extent the GD structures within the high level FG structures map to wrappers (for example the high level FG *gen-depression* (depression) structure depicted in Figure 5.4, some of the GD component structures in it which map to wrappers are *gen-presentation* (general presentation), *gen-ser-mentl-ill* (general serious mental illness) and the *gen-feel-emot* (general feeling / emotions) component structures). And as mentioned earlier as wrappers do not have any particular semantics of their own, the above observation also supports the mapping rule decision here. It is important in these discussions to distinguish between the GRiST component structures' internal and external links (see Figure 5.2). To summarise: the first link that has been established between the GRiST component structures and Markov properties is that the internal links of high level FG component structures map to Markov random fields.

Next the global Markov property of the Markov random fields are considered. This states that any two subsets of variables are conditionally independent given a separating subset. This applies to the GRiST component structures when there are three or more fixed generic component structures (or generic distinct with a generic ancestor, these mirror the behaviour of fixed generic components) that are directly linked to each other via their root concepts. If for instance we have a combination of *FG1* + *FG2* + *FG3*, then if every path between *FG1* and *FG3* goes through *FG2*, then *FG1* is conditionally independent of *FG3*. The rationale behind this for the GRiST component structures is that, any fixed generic component structure *FG2* that separates via every path *FG1* and *FG2* essentially means that the cumulative influence that *FG1* ought to have on *FG3* is contained in *FG2* (in a similar manner to Bayesian belief networks where a child is independent of its non-descendents given its parents – the cumulative effect/influence of these non-descendents – via its ancestors - is encapsulated in the parent nodes). Alternatively, as in a FG structure the generic root concept that is the point of reference for the structure, it can be argued that in the linking between *FG1*, *FG2* and *FG3*, what is important is correctly identifying the positions of the FG structures (e.g. which of the root nodes is closest to the top risk and hence the 'defining' root node). So for instance in Figure 5.3, the Markov random field depicted will have a factor f_1 that measures the affinity between the node pairs ***a*** and ***b*** . Factor f_2 on nodes ***b*** and ***c.*** Factor f_3 on ***a*** and ***c****.*

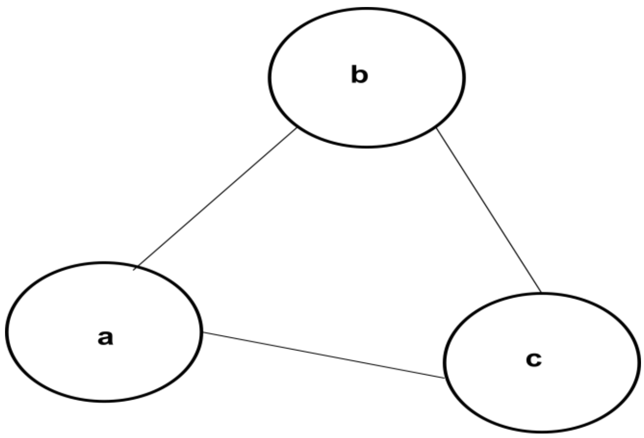


Figure 5.3: Mapping of internal nodes into Markov random field maximal clique.

The joint probability distribution of the three nodes is then:

$$P(a,b,c) = f_1(a,b)\, f_2(b,c)\, f_3(a,c).$$

In mapping the GRiST component structures to Markov random fields, care was to be taken to ensure that the correct joint probability is encoded by the resultant Markov random field.

5.4.2 Mapping to Bayesian Belief Networks

As mentioned in Chapter 2 where probabilistic graphical models were first discussed, Bayesian belief networks allow the modelling of causal relations. From the various sections in Chapter 4 it was clearly established that the GRiST knowledge structure encapsulates both causal and non causal links. Bayesian Belief Networks are used in the mapping process when considering the causal parts of the GRiST component structures. For the defining of conditional independence in Bayesian Belief Networks the notion of d-separation is used.

High level GD internal links generally map to directed graphs. This is primarily because the structure's uncertainty values/risk contribution is dependent on its neighbouring nodes and a directed graph will be able to encapsulate this dependency structure. Although high level FG internal links map to undirected graphs, high level FG component structure's external links (see Figure 5.2) map to directed graphs, this is because as a whole, the high level FG components contribute in a causal manner to the overall top risk. However, the point that is being made here stems from the fact that the overall contribution of all the various component structures is geared towards the determination of the assessment of the top risk (e.g. suicide, harm to others and so on). Again this is based on the fact that the knowledge engineering task addressed by the domain experts doing the knowledge elicitation process for GRiST was to determine the risk factors and how they are structured. As such we can assume that the knowledge structure obtained from the process is the one underpinning risk assessments and that these are dependent on cues. Therefore the probability relationship exists such that P(Category|Cues). High level GD external links also map to directed graphs for the same reasons given above for the high level FG external links.

For a GD component structure that is to be mapped to a Bayesian Belief Network the following steps need to be considered:

- Removal of any redundant nodes.
- However even if a node is thought to be redundant, special care must be taken in the modelling/design decisions. If for instance a node is removed and its internal nodes linked directly to the node on the next level of the hierarchy, then the new set of (in)dependences will be between the removed node's internal nodes and the new node they link into. However because of the removal of the node, its internal nodes will now have additional and new sibling nodes. The issue now is then that if the relationship between these new siblings and the removed node's internal

nodes become dependent, the graph might now represent a different set of independency assertions from the original component structure. However this is not an issue in the GRiST mapping because the removed node's internal nodes only become dependent on their new sibling nodes if the concept node they now link into (in the direction of the top risk) is observed and since in GRiST this cannot be the case the independency assertions remain the same, in spite of the graph reduction.

- Where nodes are removed re-link the nodes to an un-attached node in the next level. To determine the type of link to use consider the relationship types of the nodes that linked to the redundant node both a level up and down. If either one of these relationship types was a causal relationship type then use a directed edge.
- For converging nodes (the direction being considered, is going up the hierarchy), given the concept on top, the siblings that link to it become conditionally dependent on each other, due to d-separation. This result is similar to and tallies with the GRiST Markov random field solution. One can revisit the definition of d-separation in section 3.2.2 on page 47.
- If the link between the nodes is serial i.e. goes from $X \rightarrow Y \rightarrow Z$ then by d-separation, given Y, X and Z become conditionally independent. This tallies with the independence property of the GRiST knowledge structure because this simply means that it is taken into account that the contribution of Z to X is already contained in Y.
- Diverging links do not occur in the GRiST knowledge structure and as such have not been treated.

We now consider some additional concepts that occur in relation to Bayesian belief networks that will have an impact on the mapping of relevant GRiST component structures to a Bayesian Belief Network.

5.4.2.1 Independency Map (I-Map)

The following definitions have been adapted from (Koller and Friedman, 2009). The set of independence associations with a particular joint probability distribution *D* can be defined as follows:

Let D be a joint probability distribution over a graph G comprising of X, Y and Z, the I(D) is the set of independence associations of the form $X \coprod Y \mid Z$ *that holds in D. And*

I(bbn_1) represents the independencies associated with a particular Bayesian Belief Network (bbn_1).

Where I(bbn_1) $\subseteq$ I(D), bbn_1 is said to be the independency map for D.

The above relates to a GRiST component structure's mapping process as follows. For a GRiST component structure to be mapped to a Bayesian Belief Network, the set of independencies associated with the GRiST component structure's distribution must be satisfied by the Bayesian belief network's local independencies. Let us consider an example to aid our answering this question. Let the GRiST component structure to be mapped to a Bayesian Belief Network be a GD structure (gd_1) with relationship type of *contribute-to* between all its nodes, and the Bayesian Belief Network to be mapped to be bbn_1. To check that *I(bbn_1) $\subseteq$ I(gd_1),* we need to clearly define *I(bbn_1).*

- As a result of the direction of causality, the GD structure is seen to be made up of a series of *V* structures, which represent "common effect", in this context two nodes have common effect when they are both linked to a third node with a directed edge going from them to the third node (an example of this is depicted in figure 3.4(e)). The following constitute the independencies associated with the GD structure:
  1. A node *X* in a higher level *L* in the hierarchical structure, not independent of the nodes in a level *L-1* that are directly linked to it.
  2. Nodes linked via paths are not independent of each other. However along a path with nodes *X -> Y -> Z,* the contribution from *X* to *Z* is contained and passed to *Z* via *Y* and as such *Z* is conditionally independent of *X* given *Y*.

We now need to ascertain that *I(bbn_1) $\subseteq$ I(gd_1)* holds by highlighting the ways in which they correlate

- The local Markov property of a Bayesian Belief Network that states that any variable is conditionally independent of its non descendents given its parents directly maps to point #2 above (Korb and Nicholson, 2003).
- The *V* structure in the GD component structure maps directly to the global independence properties represented by d-separation. In particular the common effect d-separation, where *X* can influence *Y* via *Z* only if *Z* is observed or one of its descendents is observed. And this correlates directly with #2.

We therefore see $I(bbn_1) \subseteq I(gd_1)$ holds true.

5.4.3 Chain Graph Markov Properties

Chain graphs model the relations between variables using both directed and undirected edges with the constraint that they do not have semi-directed cycles. In representing the variables within a domain and the relationships between them, these can only be represented by a chain graph if they have inherent within their structure a dependence chain (Krause, 1998). A dependence chain refers to the capacity to order the variables and the relationships that exist between them in such a way that they can be partitioned into disjoint subsets (or blocks), and within each of the subsets where links exist between variables in the same subset, the relationship is associative (i.e. the links are non causal, represented by lines) and between subsets where links exists between variables the links are directed edges depicting causal relations. Furthermore for the links between subsets i.e. the directed edges, the arrows all need to be pointing in the same general direction (traditionally from right to left). However due to space constraints or for aesthetic reasons they are sometimes drawn from top to bottom or vice versa.

In developing chain graphs all the variables in the domain are initially split into one of two groups consisting of explanatory and response variables, where the explanatory variables are the variables that influence other variables and thereby generate a response in these variables (which are therefore known as the response variables). Explanatory variables are the variables that 'explain' the response variables, whilst the response variables measure the outcomes. For instance in GRiST a response variable will be the *suicide* concept node. The notion of explanatory and response variables is closely linked to causation and can imply causation but this is not necessarily always the case. There is no limit to the number of explanatory variables that can be linked to a response variable and the same is true for the number of response variables that an explanatory variable can be linked to, these are all driven by the domain being modelled. A simple example of each of the variables would be the link between *Suicide* and *Depression*, in this case *Suicide* is the response variable and *Depression* the explanatory variable. In addition to the direct influences between variable, within a chain graph the indirect influences between models and the association structure that exists between explanatory variables are also modelled (Buntine, 1995).

In some cases, and this is definitely the case for the GRiST structure, explanatory variables (also known as influence variables) can in some instances be further split into intermediate response variables and the influence nodes of the intermediate response variables. For instance, considering a larger subset of the GRiST suicide knowledge structure; *Suicide* can be taken as the main response variable, whilst *Depression* is seen as an intermediate response variable and the variables linked to the *Depression* node can also be split into intermediate and explanatory variables depending on their locations and functions in the structure. For example from Figure 5.4 *gen-voices-type* and *gen-presentation* are intermediate nodes.

Figure 5.4: GRiST knowledge structure depicting *depression* and its internal nodes (‘*g’ and ‘gd’* denote ‘FG’ and ‘GD’ components respectively ; whist ‘gdat’ and ‘gdd’ are the respective datum node equivalents).

In the GRiST model, a relationship pattern that is seen to reoccur at different locations in the knowledge structure is the relationship between component structures root node Z and its internal nodes X and Y. This pattern can be interpreted to expose a symmetric relationship between X and Y with a latent child variable L. For instance the diagram on the left of figure 5.5 depicts the original relationship between X and Y as modelled in the GRiST knowledge structure (note that in the original diagram, arrows, do not necessarily depict causality but rather depict the direction of propagation of the membership grade values). Whereas the diagram on the right illustrates the existence of a symmetric relationship between the two variables as a result of a common latent child L inferred from the relations between the variables. The relationship between the newly added latent child L and child variable Z is now depicted as a symmetric one, this is because the latent child L represents the cumulative influence of variables X and Y. Richardson (1999) outlines three ways in which two variables can be symmetrically related as (1) if the two variables have a common cause (2) if they are both causes of some variable (3) if they are both causes of each other. The pattern found in some parts of GRiST discussed above falls under (1).

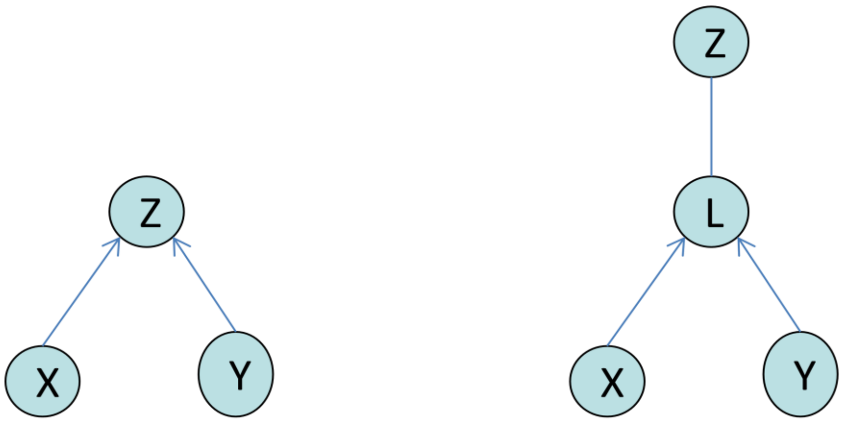


Figure 5.5: Illustration of symmetric relationship between variables with addition of latent child variable.

5.5 Impact of Relations on the Mapping Rules

In this section the development of the mapping rules taking into consideration the impact of the relationship types on the mapping rules is carried out. The focus is on the mapping of the high level (non pure) generic component structures and the non generic component structures. The low level (pure) generic component structures are being intentionally omitted, due to the fact that the probability building blocks that they map to are determined by the root node to which they are internal nodes. What this means for instance to a low level GD component structure is the following. Even if on applying the mapping rules the resultant probability building block should be a directed graph, if the low level GD structure constitutes a set of internal nodes to a FG structure. The resultant directed graph is overridden and the rules that apply to a FG structure will be what would hold for the GD structure. This is a direct result of the constraints of the component structures. This also highlights part of the importance of breaking down the component structures into both high and low level structures. Some rules override others for instance regardless of whether or not a wrapper has causal relations between its nodes it maps to a Bayesian Belief Network (see the mapping example in Figure 5.9). A similar rule applies to high level FGs which however map to Markov random fields (see Figure 5.6). Figure 5.7 depicts some unpermitted combinations, whilst Figure 5.9 depicts the high level GD.

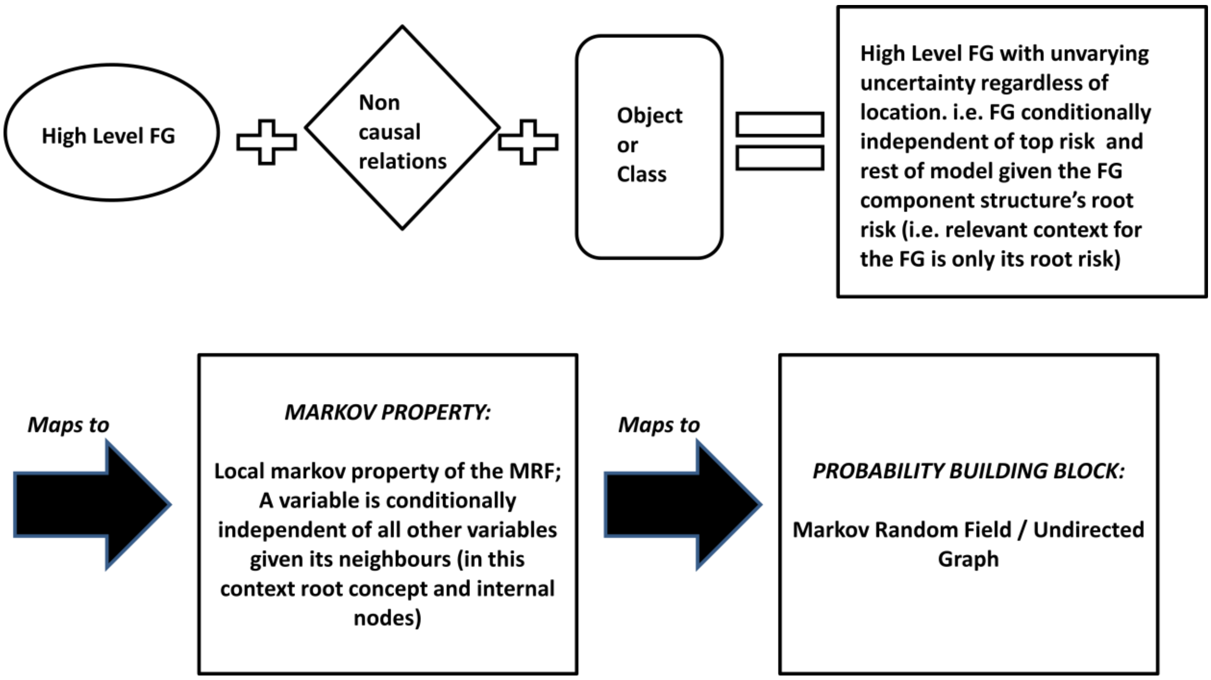


Figure 5.6: Mapping rule for high level FG that map to objects or classes with non causal relations.

From the exploration of the GRiST knowledge structure it was found that generally the generic component structure that map to classes and objects are FGs. This tallies with the expected theory as classes and objects are able to control their own internal RIs. And as mentioned earlier this is the precisely the case for FGs where their root concept is always seen to be the context that influences them and not the top risk as in the case of GDs. However, this does not mean that GDs cannot be objects or classes; there are examples in the GRiST knowledge structure of these.

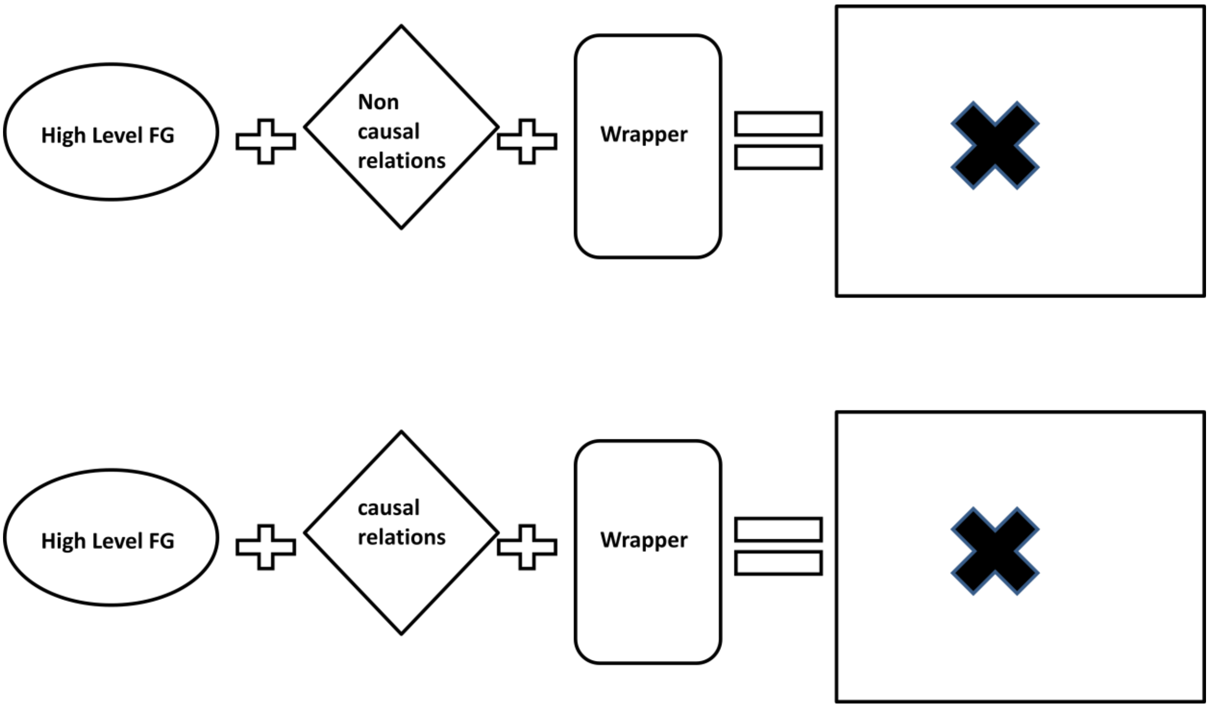


Figure 5.7: Depictions of unpermitted combinations for high level FG mappings.

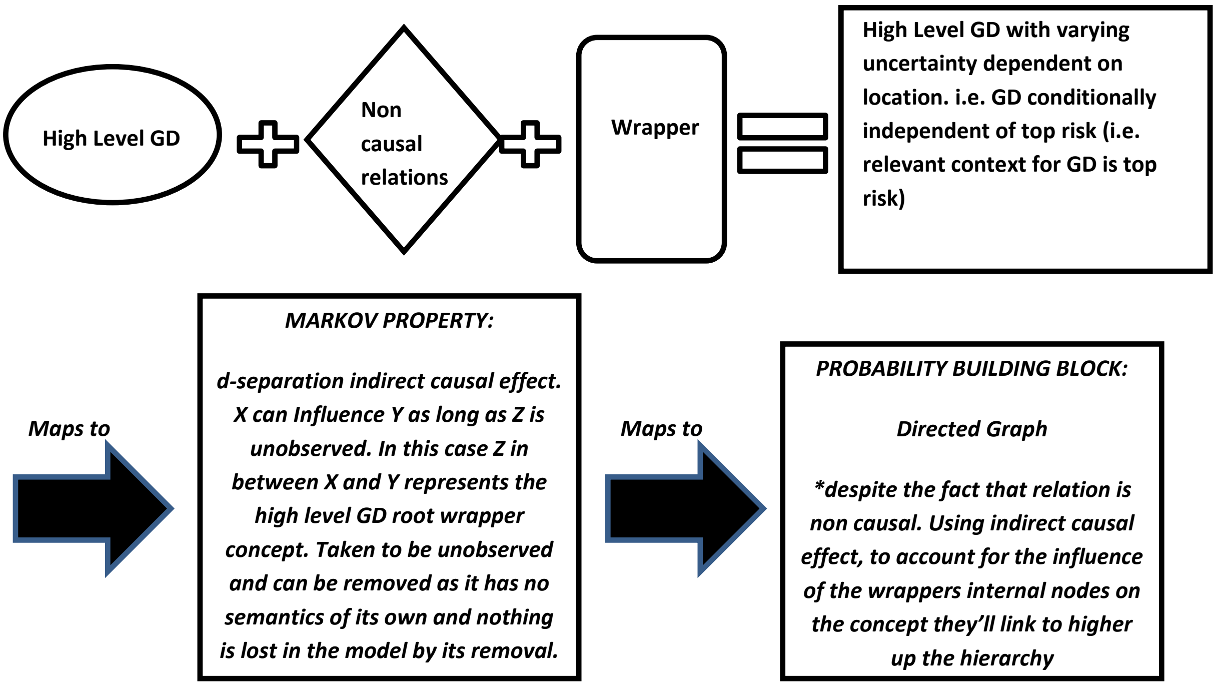


Figure 5.8: Mapping rule for high level GD that map to wrappers and have non causal relations.

The interesting thing with these cases is that what we have found is that wherever a GD structure falls into the category of a class or an object, it is always a low level GD structure contained within another generic FG component structure (i.e. its root concept is a FG) and as such its characteristic traits are overridden by those of its root FG structure. An example of this from the GRiST knowledge structure is a person's perspective of self worth (*gen-self-worth-p* in Figure 5.4), which is a GD component structure classified as an object but with a root concept *depression* which is a FG component structure. The above is illustrated in Figure 5.11.

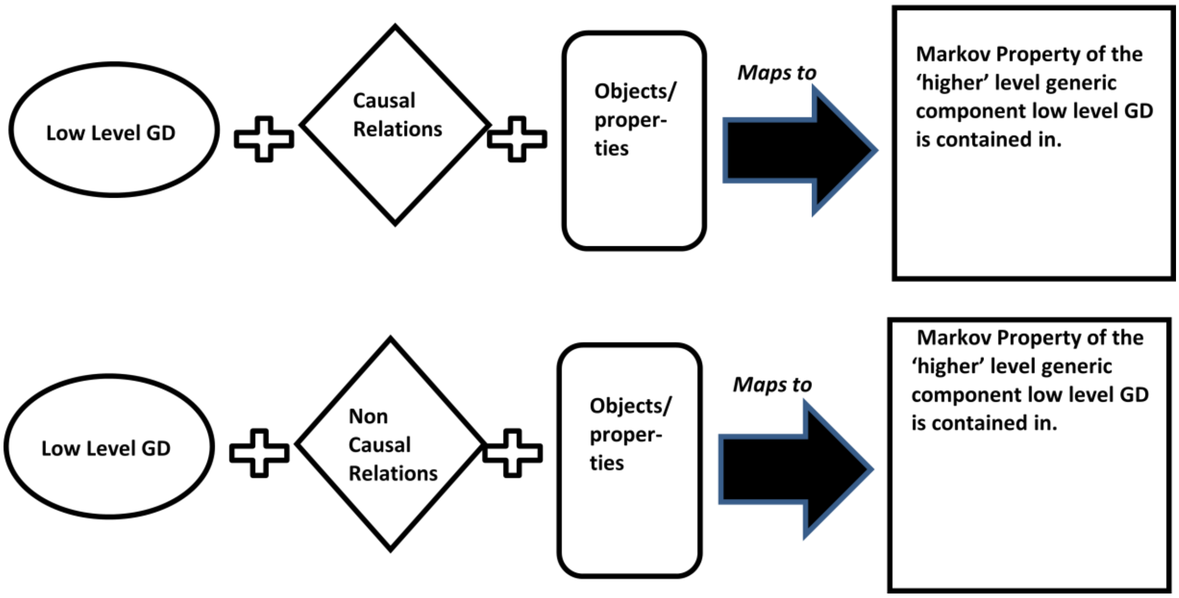


Figure 5.9: Mapping rules for low level GDs that map to objects or properties.

5.6 Summary of Mapping Rules to Probability Building Blocks

In this section, the mapping rules from GRiST component structures can be summarised as follows:

- Low level GD or FG, map to the probabilistic graphical model of the 'higher root node' that determines their behaviour.
- High level FG component structures map to Markov random fields (here the reference is to their internal links).
- High level FG component structures external links map to Bayesian Belief Networks.
- High level GD component structures map to Bayesian Belief Networks.

5.7 From Probability Building Blocks to the GRiST Chain Graph

Chain graphs are graphical models which allow both directed and undirected graphs with the constraint that they do not have semi directed cycles (Drton, 2009). Linking two variables in a chain graph with a directed edge implies that the relationship between them is causal, and the direction of the edge is from cause to effect. On the other hand variables that are linked with an undirected edge do not have a causal relationship but have an associative relationship (in a similar manner to Markov random fields). As a result of the inherent causal and associative relationships contained within the GRiST knowledge structure, which are also clearly seen in the mapping to the building block probability graphs (discussed earlier), it makes logical sense to model this knowledge structure using a probability chain graph. More in-depth discussions on the chain graph can be seen in the earlier section on probability graphical models (see Chapter Two and (Lauritzen and Wermuth (1989)). The approach that we are taking to develop the GRiST chain graph is to construct it from the building block probability graphs. To ensure that this is done correctly we will start by looking at the standard components that are defined for a chain graph.

The following definitions are taken from Buntine (1995:48):

Definition 1 "*Given a chain graph G over some variables X, the chain components are the coarsest mutually exclusive partition of X where the set of subgraphs induced by the partition are connected and undirected".*

In this context the coarsest mutually exclusive partition of *X* refers to the largest partition that can be obtained from the chain graph with the nodes within the partition connected by undirected edges. The chain components of a chain graph can be found simply by deleting from the graph all directed arcs, leaving only the chain components (Drton, 2009).

Definition 2 "*Given a chain graph G over some variables X, the component subgraphs are a coarser partition of variables X than the chain components, and are the coarsest partition where the set of subgraphs induced by the partition are connected, undirected or directed (but not mixed) subgraphs of the chain graph G".*

From definition 2, we see that chain graphs naturally decompose into component subgraphs. The component subgraphs are the chain graph's maximal directed and undirected parts (Buntine, 1995). Therefore for the composition/construction of the GRiST chain graph we need an additional step, where we ensure that from the probability building blocks we obtain the maximal directed and undirected graphs.

To obtain the maximal directed and undirected graphs, once we have obtained all our building blocks from the component structures, we need to then identify those which ought to be combined together to obtain the maximal directed or undirected (but not mixed) subgraph that they represent.

In summary this means we need to

- link together all directed building block graphs that are meant to be joined together so as to form the maximal directed graphs and likewise for the undirected graphs.
- then for all probability building blocks that contain mixed edges, we need to decompose them into their maximal subgraphs (i.e. the coarsest partition that they can split into where each subgraph has the same type of link; directed or undirected).

For every chain graph there is a unique set of component subgraphs. The algorithm for finding these subgraphs and the subsequent proof for it can be found in (Buntine, 1995). In our case we are attempting to do the reverse of what has been done there i.e. we are constructing the chain graph from the component subgraphs obtained via the probability building blocks. Below we consider the decomposition of a chain graph into component subgraphs and then consider the composition of chain graphs from component subgraphs.

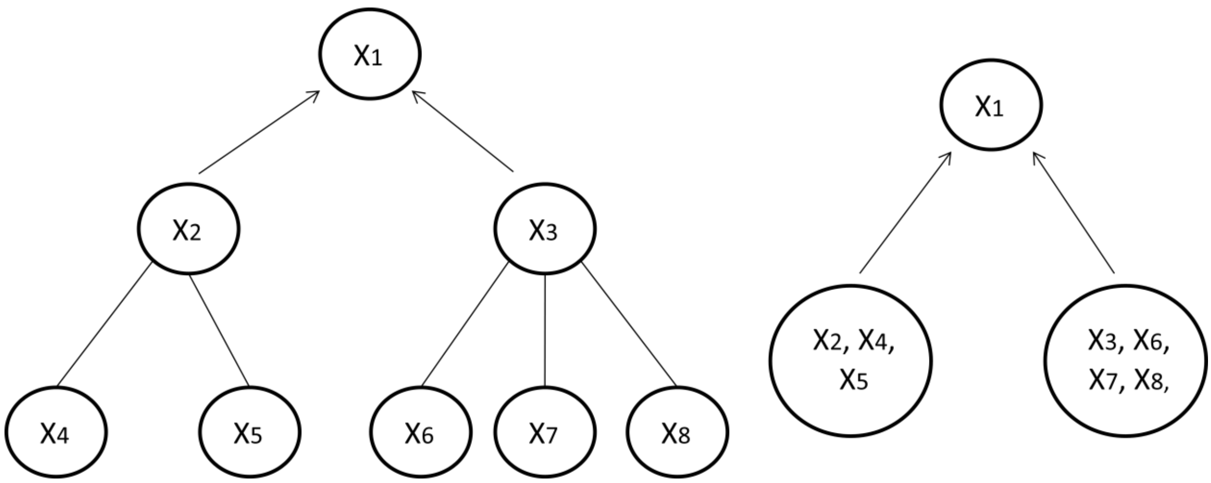


Figure 5.10: Decomposing a Chain Graph.

In the chain graph depicted on the left of Figure 5.12, from definition 1 above the component chains are $\{X_2,X_4\}$, $\{X_2,X_5\}$, $\{X_1\}$, $\{X_3,X_6\}$, $\{X_3,X_7\}$.and $\{X_3,X_8\}$. Whilst from definition 2 the component subgraphs are $\{X_2,X_4,X_5\}$, $\{X_1\}$ and $\{X_3,X_6,X_7,X_8\}$. The graph at the right hand side of Figure 5.12, depicts the directed master graph of the chain graph. This master graph is a Bayesian Belief Network showing how the component subgraphs are pierced together. The possibility of deriving a Bayesian Belief Network from the final chain graph is worth noting as it opens up the range of possible tools that can be used. A definition for the interpretation of a chain graph that supports the above is given by Buntine (1995).

The two main challenges are 1) how to obtain valid and correct component subgraphs from the probability building blocks 2) how to combine these subgraphs to obtain the correct chain graph. For the GRiST development the probability building blocks that the component structure map to directly correspond to the component subgraphs of definition 2, and by combining these the final chain graph is obtained.

5.8 Conclusion

In this chapter the mapping rules for the conversion from the GRiST component structures to probability building blocks have been developed. These rules were constructed by further analysing the various areas of the GRiST knowledge structure that give information regarding the semantics engrained in the various GRiST component sections. Concepts such as causality and conditional independency within the GRiST knowledge structure were also considered and how these map to the Markov properties of the probability building blocks. Identified correlations between the GRiST knowledge structure semantics and the probability building blocks Markov properties were then used to develop the mapping rules that will drive the conversion process.

The chapter then concluded by examining chain graphs and their development from chain components and component subgraphs and what these correspond to in the GRiST domain. In the next chapter (i.e. Chapter 6) the implementation process of the GRiST chain graph is discussed.

Chapter Six

6. The GRiST Chain Graph for Mental Health Risk Assessments

In this chapter we discuss the implementation of the GRiST chain graph. In particular we discuss details of the various algorithms used at various stages of the development process. Details of the tool and programs used to facilitate the implementation process are also discussed.

This chapter begins with a brief introduction to the data used in this research. This is then followed by a section outlining the various programs and tools used for the implementation process. This is followed by a discussion of the two main approaches used for the implementation of the GRiST chain graph, namely the embedded graph and the factor graph approaches. The embedded graph approach was primarily to facilitate parameter learning from the GRiST data, whilst the factor graph approach was for the inference. The chapter goes on to examine the methods and how they were utilised to develop the final probabilistic graphical model for the mental health risk assessments. In this chapter the term undirected graphs and Markov random fields are used interchangeably, and likewise for directed graphs and Bayesian belief networks.

6.1 Introduction to the Data

The data used in this research consists of 9417 patients on whom mental health risk assessments were performed. This was collected by clinicians during the course of their clinical risk assessments with the patients, using electronic questionnaires based on the questions listed in Appendix 2. In Appendix 2 the full list of possible questions can be seen, from the GRiST version for working-age adults. There are altogether three versions of the questionnaire designed with specific populations in mind, namely the version for working-age adults, older adults and finally the one for children and adolescents. The data used contains 138 potentially observable variables, which map directly to the GRiST datum nodes discussed in the section on the GRiST knowledge structure (Chapter 2). In addition to the values of the datum nodes, the data also contains the clinicians' expert judgements of the mental health risk level for each patient. These values become important when the validation of the implemented model is done. This will be explored in Chapter 7.

6.2 GRiST Programs

In the overall development process from the GRiST knowledge structure to the probabilistic model for risk assessments there are six main steps:

- The identification of the relationship types that exist between the GRiST knowledge structure nodes.
- The decomposing of the GRiST knowledge structure into the GRiST component structures.
- The mapping of the GRiST component structures into probability building blocks.
- The composition of the GRiST chain graph from the probability building blocks.
- The learning of the GRiST chain graph parameters from data.
- And finally the prediction of the risk assessments using the probabilistic graphical model.

Each of these steps maps to various aspects of the research. The way the complete implementation of the GRiST probabilistic graphical model has been carried out is through a series of programs that feed into one another. This facilitates the automation of sections of the development. The overall development is semi-automated with most of the processes being automated by their implementation in programs. In this section we briefly outline the various programs developed in this thesis. All together these programs facilitate the objective of providing a principled approach to translating the GRiST knowledge structure into a probabilistic graphical model to be used for mental health risk assessments. We have represented the various steps as algorithms depicting the function they perform, each of which are depicted in Figure 6.1. To add clarity each of these algorithms has been named based on their function.

This section outlining the various steps and/or programs has been added here to improve clarity by giving a general overview of the different steps. Subsequently some of these algorithms are then explored in greater detail.

The first step which we call the IDENTIFY step corresponds to the identification of the relationship types that exist between the various nodes (this was discussed in detail in Chapter 4).

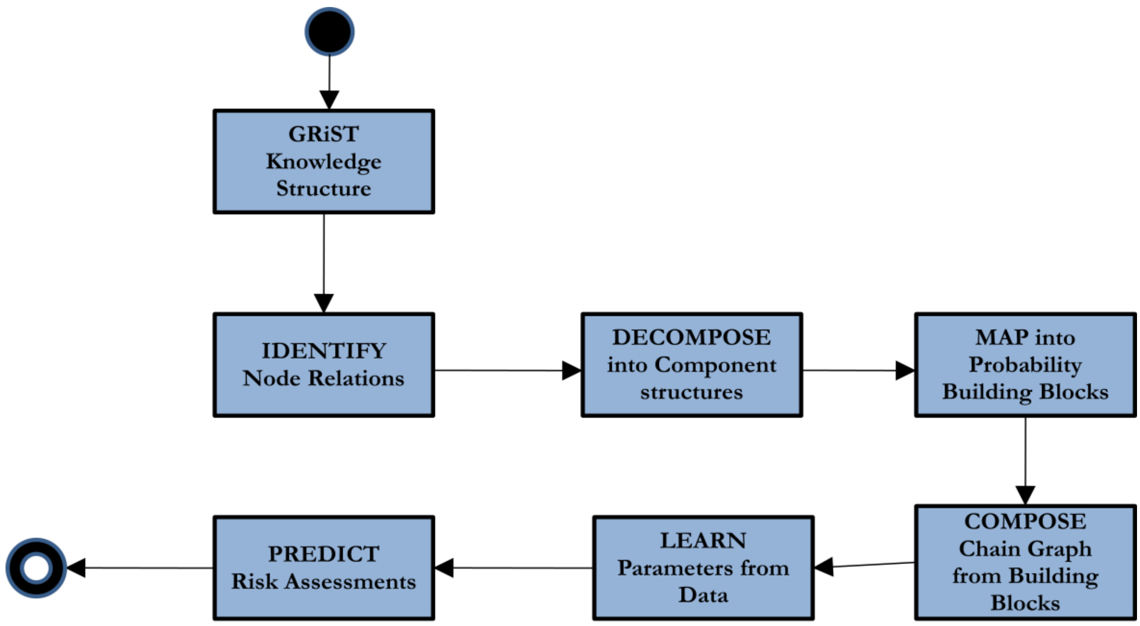


Figure 6.1: GRiST programs: the algorithms they implement.

6.2.1 IDENTIFY

Algorithm 6.1 Algorithm for identifying the relationship types between the GRiST knowledge structure nodes

```
Procedure IDENTIFY

Input: A GRiST knowledge structure GKS.

Output: GKS with set R of relationship types between every linked pair of
nodes N identified and filled.

Set R = 0;
foreach GKS pair of nodes N do
        Start from bottom of GKS tree, i.e. datum nodes D and work upwards
        through both Datum D and Concept C node pairs
foreach pair of Nodes N ({D,D}, {D,C}, {C,C}) do
        if relationship between pair is of type relation1 (i.e. is-a) then
                set R = is-a for the pair
                mark relationship type as done between this pair //node pair
                not to be revisited
         end
```

```
    if relationship between pair is of type relation2 (i.e. gives_details_of) AND R=0 for node pair then
            set R = gives_details_of for the pair
            mark relationship type as done between this pair //node pair not to be revisited
    end
    if relationship between pair is of type relation3 (i.e.contributes_to) AND R=0 for node pair then
            set R = contributes_to for the pair
            mark relationship type as done between this pair //node pair not to be revisited
    end
    if relationship between pair is of type relation4 (i.e. precedes) AND R=0 for node pair then
            set R = precedes for the pair
            mark relationship type as done between this pair //node pair not to be revisited
    end
    if relationship between pair is of type relation5 (i.e. part_of) AND R=0 for node pair then
            set R = part_of for the pair
            mark relationship type as done between this pair //node pair not to be revisited
    end
    if relationship between pair is of type relation6 (i.e. component_of) AND R=0 for node pair then
            set R = component_of for the pair
            mark relationship type as done between this pair //node pair not to be revisited
            end //in this way map all nodes from possible set of
relations until all relations for all linked nodes are set
```

```
            end
      end
  end
```

6.2.2 DECOMPOSE

The decompose program takes as input a GRiST knowledge structure and decomposes it into its constituent component structures and is implemented as a c# program. The algorithm outlines the various steps that need to be carried out to decompose the GRiST knowledge structure into its component structures. This process is motivated by the discussion on the GRiST constraints and component structures in Chapter 2 and 4.

Algorithm 6.2 Algorithm for decomposing the GRiST knowledge structure into the GRiST component structures

```
Procedure DECOMPOSE

    Input: A GRiST knowledge structure GKS.

    Output: A set of GRiST component structures C comprising of FGs, GDs and
    non generics

    Set C = 0;

    foreach GKS level l do

        Start from highest level i.e. top of tree with nodes nearest to top
        risk try

    foreach identified root node rn (i.e. type g or gd) & while embedded
    components == true do

            Add C = {component type, tr, l, primaryKey=rn,
            foreignKey=parent node}

          end

    end

end
```

6.2.3 MAP

The MAP program like the DECOMPOSE program is implemented as a c# program. It takes as input the GRiST component structures and maps them to the relevant probability building blocks using the mapping rules discussed in Chapter 5.

Algorithm 6.3 Algorithm for mapping the GRiST component structures into probability building blocks

```
Procedure MAP
      Input: GRiST Component Structure CS
      Output: Probability Building Block BB
      Set BB = 0;
      foreach GKS CS do
            if CS == high level FG then
                  BB =  MRF
            end
            else if CS == high level GD then
                  BB = BBN
            end
            else if CS == non generic then
                  BB = BBN
            end
      end
    end
```

6.2.4 COMPOSE

Algorithm 6.4 Algorithm for composing the GRiST chain graph from the probability building blocks

```
Procedure COMPOSE
    Input: Probability Building Blocks BB
    Output: GRiST Chain Graph CG
    Set CG = 0;
    foreachGRiST BB do
        Split BB into Chain Components CC
        Identify Nodes to be linked via directed edges e
        Link CC with e
    end
end
```

6.2.5 LEARN

This section covers the learning of the parameters of the probabilistic graphical models from the patient data. The entire learning process was done using the MATLAB Probabilistic Modelling Toolbox for MATLAB/Octave (PMTK, n.d.). This toolbox is discussed in a subsequent section and the processes it was used to carry out are also explored in greater detail later on in this chapter. The Expectation Maximisation algorithm is used to estimate unknown parameters and was used for the parameter learning of the GRiST probabilistic graphical models (Kjaerulff and Madsen, 2008). The algorithm is discussed in further detail in section 6.4.2.1, page 146.

Algorithm 6.5 Algorithm for learning the parameters for the GRiST chain graph from patient data

```
Procedure LEARN
    Input: Probability Building Blocks BB
    Output: Parameters for graph
    Set BB = 0;
    foreach GRiST BB do
        Learn BB parameters using Expectation Maximisation Algorithm
```

```
        end
end
```

6.2.6 PREDICT

This section relates to the prediction of risk using the final probabilistic graphical structure. Again like the LEARN algorithm it was carried out using the MATLAB Probabilistic Modelling Toolbox for MATLAB/Octave and is discussed in more detail in subsequent sections in this chapter. The junction tree and belief propagation algorithms used in the PREDICT algorithm are inference algorithms used to compute probabilities in the graphical structure (Korb and Nicholson, 2003). They are discussed further in section 6.4.3 page 150.

Algorithm 6.6 Algorithm for prediction of the mental health risk using the final GRiST probabilistic graphical model

```
Procedure PREDICT
    Input: GRiST Probabilistic Graphical Model GM
    Output: Risk predictions from the probabilistic graphical model
    Set GM = 0;
    from GRiST GM do
        For GM = BBN or MRF inference use Junction Tree / Belief Propagation
        Algorithms
        else if GM Type is Factor graph, then use Sum - Product Algorithm
        end
    end
```

The PREDICT step is operationalised using MATLAB scripts.

6.2.7 The PMTK3 Tool

In addition to the programs developed, the main tool used for the implementation of the GRiST chain graph was the Probabilistic Modelling Toolbox for MATLAB/Octave, version

3 (PMTK3) (PMTK, n.d.) and the Bayes Net Toolbox for MATLAB (BNet, n.d.). Both of these are MATLAB graphical modelling toolkits. The toolkits support a large collection of probabilistic models and algorithms and was chosen for this research because they cover in-depth the areas that pertain to this research. In the sections that follow on the algorithms used, we explore some of the functions available in the PMTK3 toolbox.

6.3 The Factor Graph Method

The first method used for the construction of the GRiST probabilistic graphical model is the factor graph approach. Using this method we convert the chain graph obtained from using the mapping rules into a factor graph. The conversion from directed, undirected and chain graphs to factor graphs has been covered in detail in Chapter 3. Building further on that the factor graph sum-product algorithm is discussed in the next section.

6.3.1 The Factor Graph Inference Algorithm

The choice of inference algorithm for the GRiST factor graph is the sum-product algorithm. The sum – product algorithm is used to perform inference on a factor graph via message passing. Messages are passed between the various variable and factor nodes of the factor graph, and the algorithm eventually terminates after each edge in the graph has had two messages passed through it in alternate directions (Kschischang et al, 2001). The sum – product algorithm uses the following rule known as the sum – product update rule:

> "The message sent from a node *v* on an edge *e* is the product of the local function at *v* (or the unit function if *v* is a variable node) with all messages received at *v* on edges *other* than *e*, summarised for the variable associated with *e*." Kschischang et al (2001:502).

In the GRiST model the messages passed potentially represent one of two things:

a) When the message is from a factor node to a variable, the message corresponds to a vector over the various possible states of the variable e.g. if the variable is *past suicide attempt* then the possible states are *yes* or *no*.
b) When the message is from a variable node x to a factor node *Y*, it relates to the probabilities that the variable node takes some value p, where the value of p is computed based on the data received from all the neighbouring nodes of x with the exception of the factor node y.

When it comes to GRiST the important thing is the assessment of risk from the predicted probabilities. However, the messages generated using the sum – product algorithm do not directly aid decision making but they make it possible to compute the marginal posterior distribution of each variable in the factor graph. This tallies with the basic task of general probabilistic inference systems i.e. the calculation of the posterior probabilities of some nodes given evidence on some nodes in the graph (Korb and Nicholson, 2003).

If the update rule is applied to the factor graph in Figure 6.2, the numbered circles illustrate the sequence of the messages generated in each stage of the sum – product algorithm on this particular factor graph. In the illustration lowercase letters are used to represent variables (e.g. w, x, y and z in Figure 6.2) whilst letter ***f*** with uppercase letters as subscripts are used to represent functions (f_A, f_B, f_c and f_D). The illustration of the use of sum-product algorithm on Figure 6.2 is based on the example given in Kschischang et al (2001).

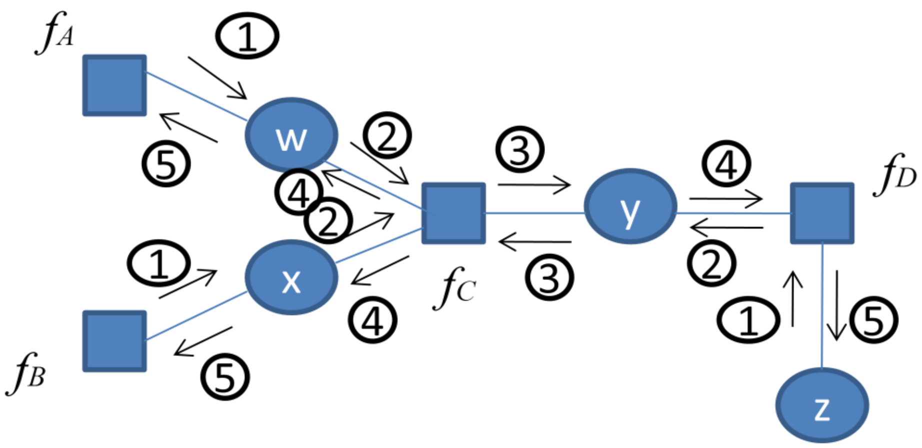


Figure 6.2: Messages generated in each stage of sum – product algorithm.

The first messages that are passed are from singly connected function nodes and variables (in this example f_A, f_B, z).

The next set of messages to be sent are from the receiving variables or function nodes in step one, these then send messages to the nodes they are connected to, all the time adhering to one of the key rules when it comes to factor graphs, namely that a node *x* cannot pass a message to another node *y* until it has received messages from all its neighbours except *y*. So each of the nodes in the factor graphs receives messages from its neighbours, takes a product, and performs summation, and then sends the resulting message to the one neighbour which it did not receive a message from. The difference between a function leading to a leaf node (e.g. W or X) and a leaf variable that has no function leading to it (e.g. Z) from the perspective of the conversion from the GRiST chain graph to factor graph is highlighted in Figure 6.3 which summaries the different conversion processes (see Chapter 3).

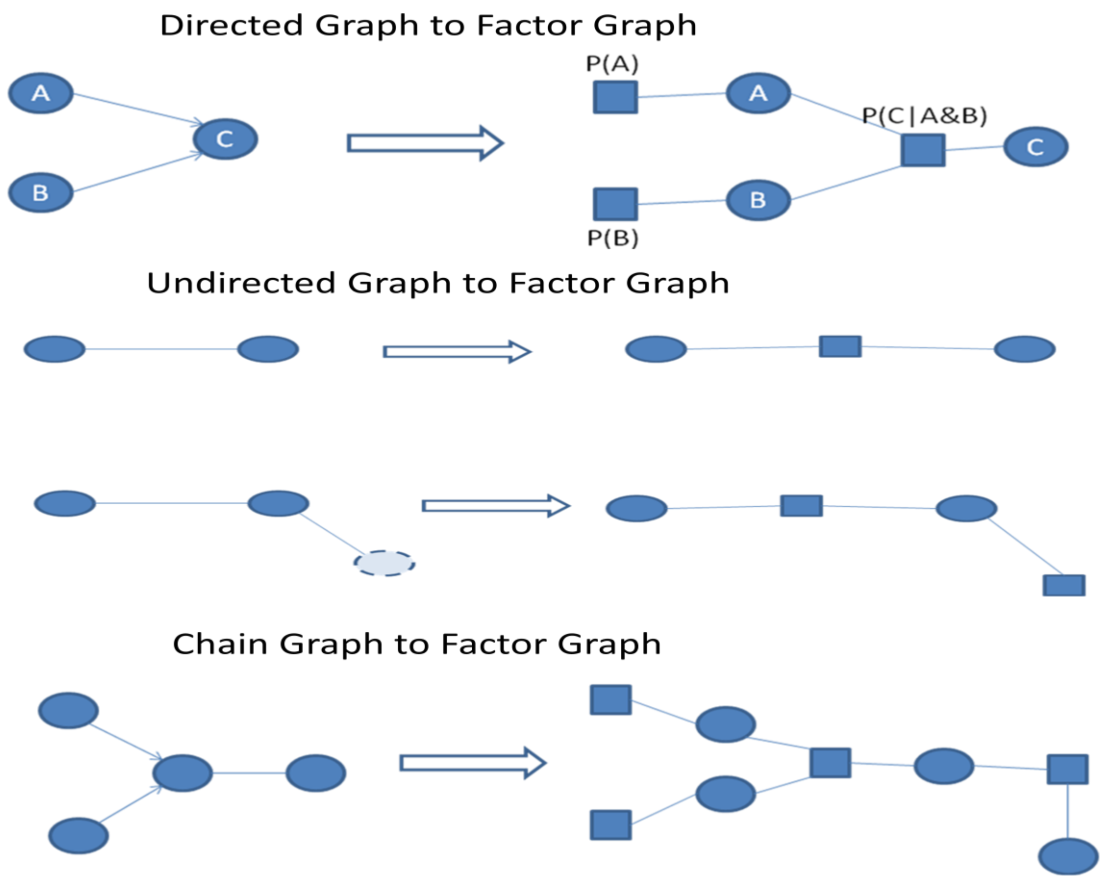


Figure 6.3: Summary of conversions from directed, undirected and chain graphs (going from top to bottom respectively).

In the sum- product algorithm there are two types of messages that can be passed, namely the variable to local function message and the local function to variable message. In a factor graph if a leaf is a variable, any message it passes to a factor node reduces to 1 whereas if a leaf is a factor node, any message it sends to a variable node *x* reduces to *f(x)* (Zhu, 2009). Whether a node is a leaf variable or has a factor node leading into it, is defined via the conversion process from chain graphs to the factor graph (see Figure 6.3) The equations representing the messages passed at various stages for a similar example can be seen in Kschischang et al (2001).

Once all the messages have been passed the termination stage involves taking a product and getting the marginal probabilities in order to compute the marginal posterior distribution of the required variable(s). One way of doing this is by taking the product of all messages directed towards the variable of interest; further details on this can be seen in Kschischang et al (2001). In this manner the required marginal posterior distribution of each required variable in the factor graph is calculated.

6.3.2 The Factor Graph Model Representation

In the PMTK3 toolbox for MATLAB, a factor graph structure is created using the PMTKs command factorGraphCreate. Factor graphs are represented in the toolbox using structs (a programming structure containing different components and values). The PMTK3 factor graph struct comprises of the following:

- A bipartite undirected adjacency matrix. An adjacency matrix presents a way to encode the structure of a graphical model. The values in the intersections of the rows and columns of the matrix are used to depict whether or not a link exists between any two nodes in the structure. This is done by the addition of a number e.g. ‘1’ to represent the existence of a link and ‘0’ the non-existence of any link. For example Figure 6.4 depicts a simple directed graph and its corresponding adjacency matrix below it. In this directed graph there are only two edges i.e. the edge between nodes (1) and (3) and the second edge between (2) and (3). The direction of any links is also encapsulated in the matrix. For factor graphs their corresponding adjacency matrices are undirected.
- An array of factors, where each factor is represented as a tabular factor; the PMTK3 tabularFactorCreate command is used to create these.
- Number of states (nstates), where nstates(x) represents the number of states that variable x can have.
- Node factors - factors linked to only one variable. Examples of this can be seen in Figure 6.2 where f_A and f_B are node factors as they are both only linked to a single variable each (nodes w and x respectively).
- Edge factors - factors linked to more than one variable. An example from Figure 6.2 is factor f_c which is linked to nodes x, y and w.
- Round - indices into the adjacency matrix that indicate nodes.
- Square - indices into the adjacency matrix that indicate factors.

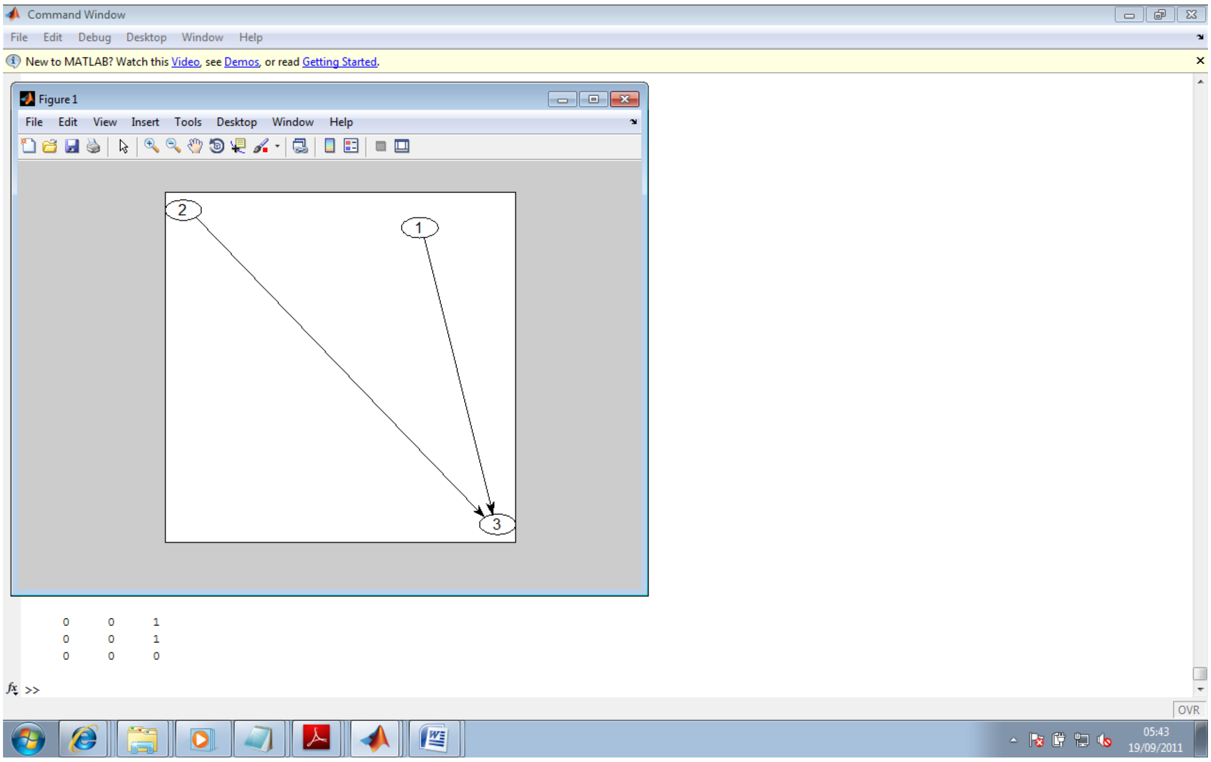


Figure 6.4: Screenshot of a simple directed graph and its corresponding adjacency matrix as depicted using the PMTK3 MATLAB toolbox.

After the creation of the factor graph using the PMTK3 toolbox, the learning of graphical structure parameters is done using the Expectation Maximisation algorithm (discussed later in the chapter), after which the inference algorithm is applied to the factor graph to compute the marginal posterior distributions of the unobserved variables and that of the top risk. More details on the learning of parameters using the toolbox and the rationale behind the choice of the algorithm used are given in the next section where we start to explore the embedded graph approach to the construction of the GRiST graphical model. The GRiST chain graph was constructed using two methods (i.e. the embedded method and the factor graph) for two main objectives 1) to learn the model parameters from the embedded graph and 2) to generate the required marginal probabilities from the factor graph by applying the inference algorithms to it. However, other advantages were obtained from the embedded graph, advantages such as being able to use it to explore relations within chain graph blocks and between chain graph blocks. So to summarise this, the embedded graph method's primary purpose is for learning the parameters and the factor graph for inference. All discussions and analyses of the results obtained from the GRiST chain graph are left till Chapter 7, the analysis and results chapter.

6.4 The Embedded Graph Method

The second approach used to develop the GRiST mental health assessment is that of an embedded graph. Some previous work has been done using the idea of embedded graphical models and mixture trees (Murphy and Nefian, 2001; Meila and Jordan, 2001). Murphy and Nefian (2001) explore the development of an embedded graphical model of Markov random fields where each node is itself a graphical model (i.e. a Markov random field). Embedded graphical models make it possible to construct complex models in a step wise fashion. So depending on the number of levels in the hierarchical structure being modelled the construction process itself can be broken down into several steps. For instance a step can comprise of the modelling of all nodes in a particular level in the hierarchy initially independent of the rest of the structure and then the results from this are fed into the next level and so on.

The primary purpose of the embedded model is to facilitate the parameter learning from data. However, it also served as an additional layer of evaluation and for comparison purposes.

To illustrate the design of embedded graphs, see Figure 6.5 which depicts a subsection of the GRiST knowledge structure. Figure 6.6 on the other hand depicts the same knowledge structure (as that of Figure 6.5) but as an embedded knowledge structure with some of the GRiST component structures represented as being contained within other component structures.

In Figure 6.6 we see the nodes from Figure 6.5 grouped together in composite nodes that can contain other composite nodes within them. An example of this from Figure 6.5 is the fixed generic component structure *gen-app-diet* that is contained within the generic distinct *gen-currnt-bhv*. However in cases like this (because of the semantics represented by the GRiST knowledge structure) the most important structures are the structures closest to the top risk. This is because a structure’s root node provides the point of reference for all the structures contained within it.

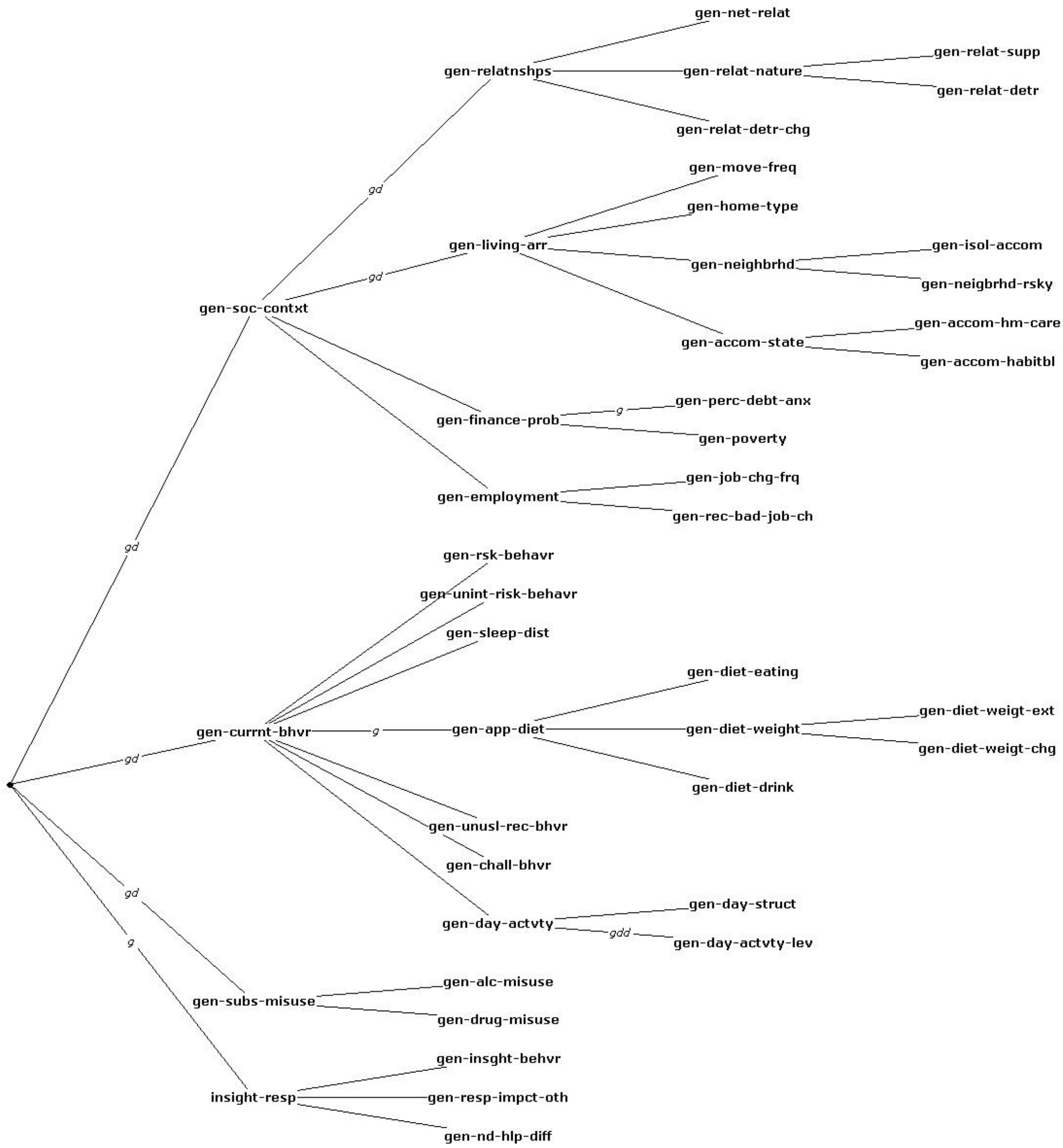


Figure 6.5: Non embedded subsection of GRiST knowledge structure (‘*g’ and ‘gd’* denote ‘FG’ and ‘GD’ components respectively).

Therefore in the cited example there are four equally important structures, an example of which is the generic distinct structure *gen-currnt-bhv.* From Figure 6.5, we identify five generic distinct component structures and two fixed generic component structures, which we depict in Figure 6.6 (left and middle diagrams).

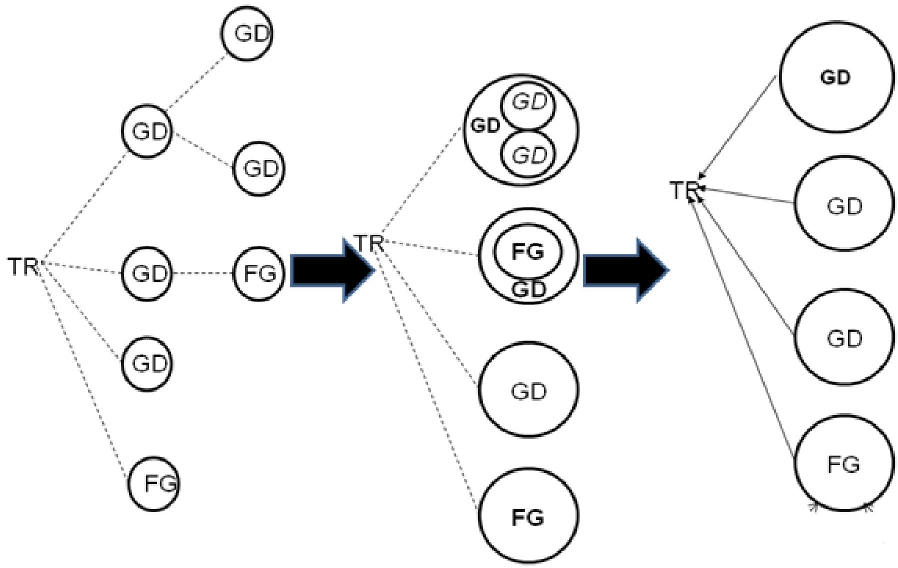


Figure 6.6: Diagram depicting subsection of GRiST knowledge structure from Figure 6.5, with component structures drawn (note that the non generic nodes which do not fall into either one of the component structures have been left out of this diagram but not the final model). TR = Top Risk.

The concept behind the embedded graphical model approach is similar to the component structures one of Figure 6.5. However, the main difference that exists between them is that the nodes represented in the embedded graph are not component structures but probability building blocks. The embedded graph approach can be summarised as follows:

From the probability building blocks mapped from the GRiST component structures (i.e. directed and undirected graphs) a two step method is used. Initially each identified probability building block (i.e. directed or undirected graph) is represented in the overall graphical model as a composite variable. This results in an embedded model where each node can itself represent a graphical model. The second layer is then reached when we model and consider an individual sub-tree. The uncertainty contribution from each node (i.e. embedded graphical model) is then plugged into an overall graph. The overall top risk for the top root (e.g. *suicide*) is then obtained using this overall graph which comprises of nodes that can also themselves be graphical models. In the next subsections we explore the implementation of the probability building blocks and the overall embedded graphical model (i.e. the LEARN and PREDICT algorithms outlined in section 6.2).

The focus in this section is on the methods that apply to the embedded graph approach. To implement the LEARN algorithm for the embedded approach, the probability building blocks that make up the entire overall embedded graphical model needed to be identified and represented as models. Recall that when it comes to context and the mapping rules (Chapter 5), the most important component structures are the high level structures. The initial step was the identification of all the high level component structures in the model and the probability building blocks that they map to (using the mapping rules). Table 6.1 lists all high level component structures relating to Suicide risk for the GRiST knowledge structure.

Table 6.1: The GRiST suicide knowledge structure high level components and corresponding probability building block types

High Level Component Structure	**Probability Building Block Type**
insight-resp	Undirected Graph
sn-appearnce	Undirected Graph
gen-impaird	Undirected Graph
gen-depression	Undirected Graph
gen-meds-therpy	Undirected Graph
gen-presentation	Directed Graph
gen-feel-emot	Directed Graph
gen-self-worth-p	Directed Graph
gen-personality	Directed Graph
gen-eng-world	Directed Graph
gen-ser-ment-ill	Directed Graph
gen-phys-hlth-prb	Directed Graph
adv-life-event	Directed Graph
gen-demog	Directed Graph
gen-soc-contxt	Directed Graph
gen-currnt-bhvr	Directed Graph
gen-subs-misuse	Directed Graph

The directed probability graphs identified in Table 6.1 were then each modelled using the PMTK2 and the Bnet MATLAB toolboxes. The probabilistic results obtained for each subgraph was then plugged into an overall embedded graph. This embedded graph was also itself modelled using the toolbox and then used to obtain the probabilistic risk prediction results. We now discuss how each of the directed probabilistic building blocks were implemented using the MATLAB toolkits.

6.4.1 Graph Model Representation

Similarly to the factor graph approach, each of the structures were represented via the use of an adjacency matrix. A program was implemented that takes in as input the XML document representing each probability building block and then gives as output files for each probability building block, its corresponding adjacency model. These models were then loaded into MATLAB, along with the data file containing the patient cases in the relevant probability building block. The MATLAB, the Bnet and the PMTK3 toolkits provide functions to check the model at different stages. For example Figure 6.4 depicts a simple example of the results from two functions depicting both diagrammatically and in matrix format the adjacency matrix representing a structure that had been loaded into the toolbox for processing.

In PMTK3/Bnet following the importation of the adjacency matrix representing the model and the dataset, for a Bayesian Belief Network the next PMTK3 function to use is the mkRndTabularCpds. The mkRndTabularCpds function creates a cell array of tabular CPDs. The function takes in as input parameters the graphical structure (in the form of an adjacency matrix), and an array containing the list of number of states for the nodes. It then returns a conditional probability distribution as output in the form of a cell array of tabular conditional probability distributions. Initially this array starts out as a place holder for the conditional probability distributions that will be obtained when the training algorithms are applied to the model. Figure 6.7 is a screenshot of the PMTK3 MATLAB toolbox depicting a tabular conditional probability distribution structure.

After the cell of tabular conditional probability distributions has been obtained the next stage involves the creating of the directed graphical model using the PMTK3 dgmCreate command. This function takes as input the graph structure (i.e. the adjacency matrix) and the newly created array of conditional probability distribution. Once the directed graphical model is created the next step is then to train the directed graphical model and learn its parameters. This is done with a PMTK3 function dgmTrain, which takes as input the directed graphical model and the patient data.

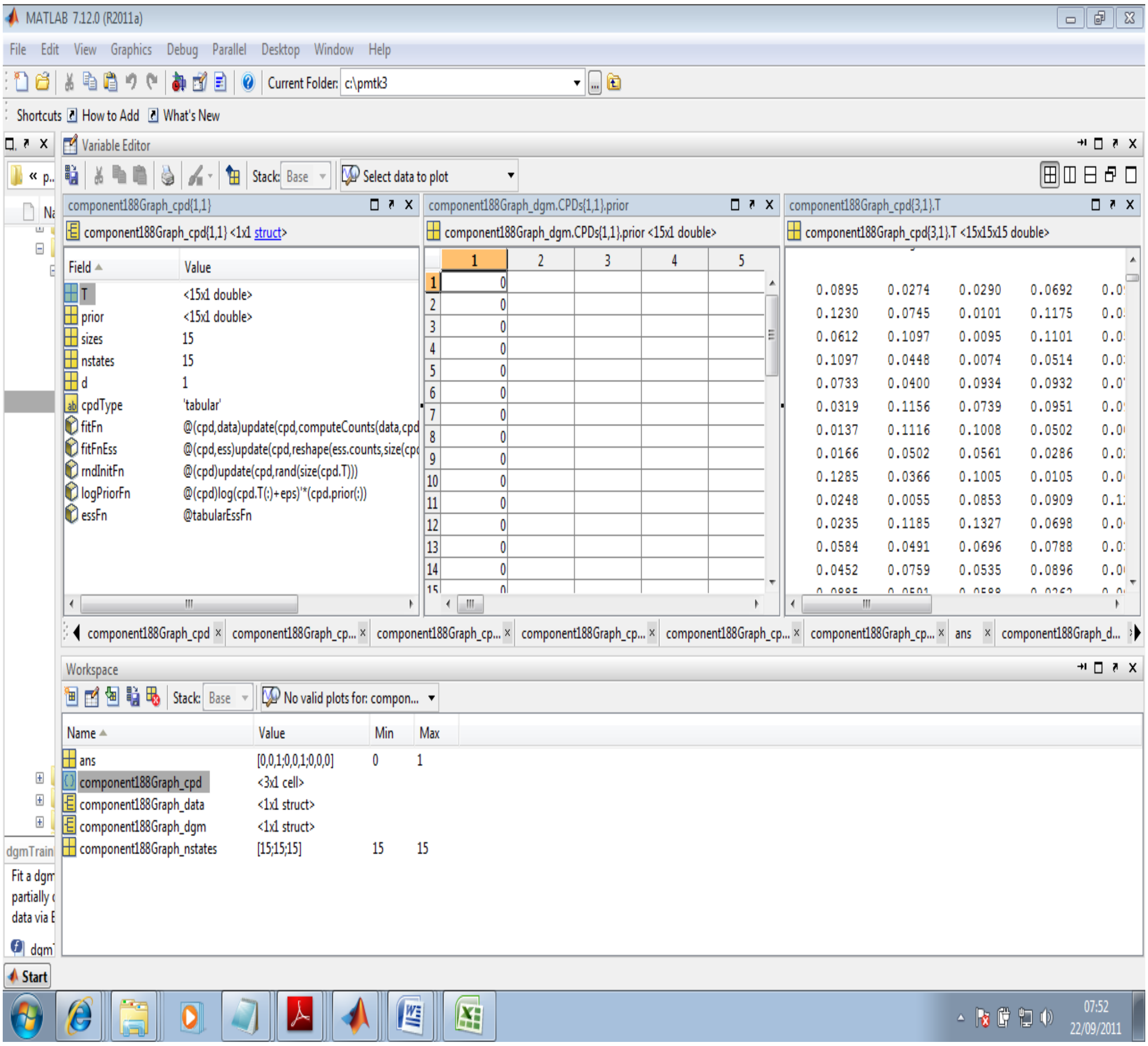


Figure 6.7: Screenshot of PMTK3 MATLAB toolbox with tabular CPD structure (left of figure), prior (middle) and post processing (right of figure) values.

As our data is incomplete (i.e. there are instances of missing data in a patient vector. Incomplete data refers to individual vectors), our choice of algorithm for the parameter estimation was the Expectation Maximization (EM) algorithm (Lauritzen, 1995). More details on this are given later in this chapter.

6.4.2 Graph Parameter Learning

Parameter learning makes it possible to obtain the parameters of a model given its structure and data for the model. Generally all parameter learning algorithms try to estimate from the data the best parameter fits to the model and a number of algorithms have been proven to be effective. However, the choice of learning algorithm should be dependent on the particular characteristic traits of the available data and the model. For instance if the available data is complete (i.e. there is no missing data) then some algorithms will perform better on them than if the data is incomplete (i.e. some data is missing). This section includes a discussion on the rationale behind the choice of learning algorithm and its implementation using the Bnet/PMTK3 toolkits.

The algorithm used for parameter learning for the directed graph probability building blocks of the GRiST chain graph was the EM algorithm. In the GRiST probability building blocks the concept nodes are unobserved variables whilst the observed variables directly correspond to the datum nodes. In the GRiST model, in addition to the concept nodes, data can also be missing as a result of the semantics of the knowledge structure. For instance filter questions in the GRiST questionnaire are linked to their underlying questions. In Figure 6.8, we see an example of this. To the question *Has there been more than one self-harm episode?*, if an answer of *no* is given then because of the semantics ingrained in the structure this will in turn render all the underlying questions (e.g. *Approximately how many episodes of self-harm have there been?*) irrelevant and so a membership grade value of 0, are automatically assigned to these underlying questions.

Our chosen algorithm is therefore the EM algorithm which is particularly good at handling incomplete data. Other algorithms that can be used for parameter learning include algorithms based on the Maximum Likelihood Estimation and Bayesian Estimation Techniques. For more details on these see [39, 103, 104].

6.4.2.1 Expectation Maximisation (EM) Algorithm

The EM algorithm was used to estimate the probability building block's parameters, by the application of the algorithm to the patient cases given the model. The EM algorithm is a variant of maximum likelihood estimates that is effective for parameter learning when the dataset is incomplete. In cases where the data set is complete, learning the parameters of the model is less complex. For instance the sufficient statistics can be calculated for datasets with complete datasets by taking a count of the frequency of occurrence of the various variables in the dataset.

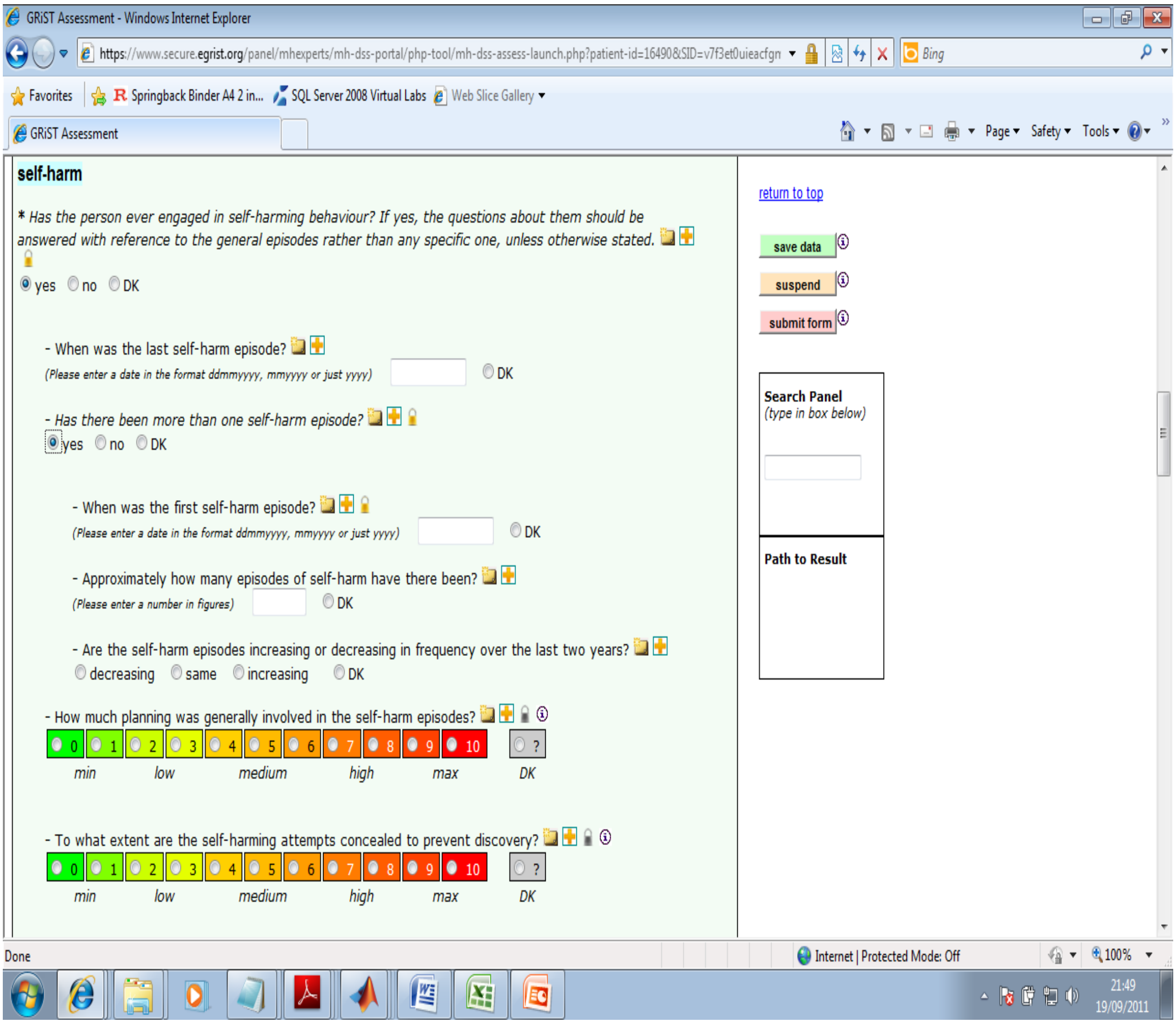


Figure 6.8: Screenshot GRiST electronic data collection tool.

The sufficient statistics show using the data to obtain a function that represents all the information needed to calculate the likelihood (Koller and Friedman, 2009). Further details on likelihood and Maximum Likelihood Expectation can be found in Koller and Friedman (2009), Jensen and Nielsen (2007) and Kjaerulff and Madsen (2008). Once the sufficient statistics for complete datasets are obtained, their parameters can be estimated by obtaining the estimation of parameters that maximise the likelihood (Koller and Friedman, 2009). However, for incomplete datasets like the GRiST data, the same approach cannot be followed as it is not possible to obtain sufficient statistics from the data. Various approaches can be considered to resolve the issues that arise when it comes to parameter estimation of incomplete datasets. Simple solutions can involve attempting to ‘complete’ the data by giving the missing data values but as mentioned by Koller and Friedman (2009) this will introduce a bias in estimated parameters.

The objective behind the EM algorithms approach is the computing of the best estimates of the parameters of the model, without introducing bias and skewed parameters. The way it accomplishes this is via an alternating two step process. These steps are the Expectation step and the Maximisation step. In the Expectation step the current parameter estimates are used to obtain expectations for the unobserved values (Jensen and Nielsen, 2007), whilst in the Maximisation step the previously completed dataset (i.e. the dataset completed via the use of the expectations in the previous Expectation step) is used to derive a new set of parameters by performing a maximum likelihood estimation (Koller and Friedman, 2009). The expectations that are calculated for the missing values in the Expectation step are calculated using the expected sufficient statistics (i.e. the expected counts) (Koller and Friedman, 2009). The expected sufficient statistics, like the full sufficient statistics (used in the case of complete datasets), need to be calculated from the complete dataset. However, as there are missing values in GRiST, the expected sufficient statistics are computed in the first instance using the initial values assigned to the missing values. The assignment of these initial values can be of any form (i.e. arbitrary). In the GRiST model this assignment is random.

As the two steps (i.e. Expectation and Maximisation) are iterated through, the estimated parameters keep continually improving until either the algorithm either converges or reaches a pre-specified end point (i.e. pre defined number of iterations).

Formally the Expectation and Maximisation steps can be represented as follows (the two definitions are taken from Kjaerulff and Madsen (2008).

For a model structure *G* the Expectation step computes the expected sufficient statistics (counts). Representing the current parameter values with θ and the observed data with *D*, Then N_{ijk} represents the count for $\left(X_i, Pa(X_i)\right) = (k, j)$ and c^l the *lth* case of the observed data *D*. Then the expected sufficient statistics is computed using the following equation in the Expectation step.

$Expectation$: $E_\theta\left(N_{ijk}\right) = \sum_{l=1}^{N} P(X_i = k, Pa(X_i) = j | c^l, \theta_i, \text{G})$. (1)

The Maximisation step then computes new estimates of the parameters θ_{ijk}^{*}

$$Maximisation\colon \theta_{ijk}^{*} = \frac{E_{\theta}(N_{ijk})}{\sum_{k=1}^{||X_i||} E_{\theta}(N_{ijk})} \ . \tag{2}$$

Algorithm 6.8 below gives a formal summary of the EM algorithm and has been adapted from Kjaerulff and Madsen (2008) and Koller and Friedman (2009)

Algorithm 6.8: EM Algorithm for Parameter Estimation

Procedure EM Algorithm

Input: G, //graphical structure over $X_1, \ldots\ldots, X_n$

θ, //set of parameters for G

D //incomplete dataset

Output: estimated parameters θ^{t} (after t iterations)

BEGIN

Initialise parameters or initialise missing values

Compute Expected Sufficient Statistics

for each t=0,1,....until convergence

// Step 1: Expectation Step

$E_{\theta}(N_{ijk}) = \sum_{l=1}^{N} P(X_i = k, pa(X_i) = j | c^{l}, \theta_i, \mathrm{G})$

//Step 2: Maximisation Step

$\theta_{ijk}^{*} = \frac{E_{\theta}(N_{ijk})}{\sum_{k=1}^{||X_i||} E_{\theta}(N_{ijk})}$

return θ_{ijk}^{*}

END

In the PMTK3 MATLAB toolbox, the EM algorithm is implemented using the dgmTrainEM function. These function input arguments are the previously created directed graphical model (Section 6.4.1) and the dataset. The parameters are then randomly initialised and these parameters used for the first iteration. The expected sufficient statistics are then computed using the PMTK3 estep function, after which the Maximisation step is performed on the data using the mstep function. In this manner the two steps of the EM algorithm are alternatively applied until the algorithm converges and at this point the final sets of estimated parameters are obtained. For the GRiST chain graphs the EM algorithm performed well and converges each time.

6.4.3 Graph Inference Algorithms

The main objective of the inference for the GRiST probabilistic graphical model is to compute the probabilities of the top risk given the values of the observed datum nodes and the entire model. The risk assessments of the top risks will then be directly inferred from these probability values. For the Suicide section of the GRiST knowledge structure there are 138 distinct datum nodes and 81 distinct concept nodes as a result of the large number of nodes in the model, the inference algorithms used needed to be computationally feasible for the GRiST probabilistic graphical model. For models with large numbers of nodes, algorithms can become computationally intractable unless simplifying assumptions are made on the model (Wemmenhove et al, 2007). However, in making assumptions care must be taken not to apply assumptions that will result in skewed results or a loss of semantics. However, for the GRiST implementation using the embedded graph approach, the issue of computational infeasibility is not an issue because the embedded graph approach makes the model more tractable as a direct result of its two stage approach. The learning algorithms in the first instance are applied to subsets of the final graph (i.e. the probability building blocks) and then in the second stage on nodes representing the different subgraphs. Performing inference on the embedded graph was not the primary goal of using this approach in addition to the factor graph approach and as such inference was only performed on the GRiST block structures as an additional layer of analysis/validation but not as the main method. Here the junction tree algorithm was used and this is described briefly below.

6.4.3.1 Junction Tree Algorithm

The junction tree algorithm is an inference algorithm that performs belief propagation. However, the difference between the junction tree algorithm and the others like the Belief Propagation algorithm (for example) is that the belief propagation in the junction tree is performed on a tree called the junction tree which is obtained by making some alterations to the original probability graph. A junction tree is obtained by conducting the following steps. These have been adapted from Korb and Nicholson (2003):

- For directed graphs moralise the graph. To moralise a graph, all the edges in the graph are converted into undirected edges and for every set of nodes that are unconnected but share a child, an undirected edge is drawn between them.
- Add the evidence (i.e. the observed data) into the model.
- Triangulate the graph. This is done by the addition of arcs to ensure that each cycle in the graph with greater than three nodes has a subcycle made up of three of its nodes (i.e. it is chordal).
- The next step is now to construct the junction tree from the triangulated graph. This is done by creating compound nodes from maximal cliques in the graph (where a maximal clique refers to a complete subgraph not contained within any other subgraph).
- Separators are added which represent the intersection points of adjacent nodes.
- New parameters are computed from the nodes in the graph and the separators.

The belief propagation algorithm is then performed on the junction tree and in this manner the probabilities are propagated along the graph.

6.4.4 Undirected Graph Model

The implementation of the probability building blocks that map to undirected graphs is very similar to that of the probability building blocks that map to directed graphs (section 6.4.1). The graph structures are represented as adjacency matrices. mrfCreate is run. This function takes in as input the graphical structure (i.e. the adjacency matrix that represents the node topology). Other input arguments include numeric matrices that represent both node and edge potentials. Also in a similar manner to the directed graphical models, the estimation of the parameters was done with the EM algorithm (function mrfTrainEm). The same inference algorithms used for the Bayesian Belief Network subgraphs were used.

6.4.5 The Complete Embedded Graph

In this section the second stage of the embedded graph approach is discussed. This stage involves bringing together the subgraphs (i.e. the probability building blocks) that we have prior to this point constructed within the Bnet/PMTK3 MATLAB toolkits) in way that some of the nodes in the overall embedded graph themselves represent the subgraphs. Using the estimated parameters learnt for the subgraphs (i.e. both directed and undirected) we construct a directed graph that represents the entire GRiST chain graph. The graph that we construct in this second stage is linked to its neighbouring nodes using directed edges in the direction of the top risk (including nodes that represent both Markov random fields and Bayesian belief networks). This is because the experts from whom the knowledge was elicited to develop the GRiST knowledge structure provided information that will lead them to believe a person was at risk. As a result of this the modelled knowledge structure is an overall causal structure in the direction of the top risk. However, within the structure both causal and non-causal relations are contained. This is seen in the Bayesian belief networks and Markov random fields probability building blocks respectively. For the inference of the full embedded graph, as it is modelled as a directed graph the same inference algorithms as for the directed subgraphs (Section 6.4.3) are used, following the same processes. The only difference between the full embedded graph and the directed subgraphs is that in this stage we obtain the probability distribution of the top risk (e.g. suicide) given the evidence (in this case the observed patient data).

6.5 Conclusion

This chapter has involved a discussion of the two approaches used for the construction of the GRiST chain graph. The main objective behind the use of the factor graph was so that the sum graph algorithm could be used for inference on the GRiST probabilistic model, whilst the second approach the embedded graph was to facilitate the learning of the parameters of the model from GRiST data. In this section the parameter estimation and inference algorithms applied to the model have also been examined. The implementation process within the PMTK3/Bnet MATLAB toolkits have also been outlined. In the next chapter (i.e. Chapter 7), we discuss the results obtained from the GRiST chain graph using the different inference algorithms and analyse the results obtained. We also validate the GRiST probabilistic graphical model using correlation analysis and the expert judgements.

Chapter Seven

7. Application of the Chain Graph to the GRiST Data and Evaluation of Results

In this chapter we discuss the testing of the model on GRiST data and evaluate the results.

In this chapter the steps followed to apply the developed model to the GRiST data and evaluations of the results are carried out. The discussion in the chapter will be done in the same sequence as the actual implementation and can be split into three main areas 1) the implementation 2) the analysis of the results and finally 3) the evaluation of the results. Throughout this chapter, selections of the component structures are used to analyse the data specifically to validate the types of graphical substructures and towards the end of the chapter the entire factor graph's predictions are tested against the actual clinical ones.

For the implementation section the areas to be discussed are:

- Construction of the GRiST chain graph.
- Parameter Learning from the GRiST data.
- The conversion from the GRiST chain graph to a factor graph.
- The use of the factor graph to run inference algorithms on the model to obtain results.

For the analysis section, the parts to be discussed are:

- The analysis of nodes within block structures and analysis of nodes between block structures.
- Analysis of the strength of the links between the nodes. Are there any particular factors that stand out or appear to be particularly significant?

For the evaluation section,

- Comparisons are made between the results obtained from the GRiST probabilistic graphical models and the expert risk judgements.
- Data and correlation analysis are also carried out on the model.

7.1 Construction of the GRiST Chain Graph

This section builds on the earlier discussions on chain graphs (i.e. from Chapters 3 and 5). To construct the GRiST chain graph from the building blocks that the component structures map to, the model was partitioned into chain graph block structures as discussed in Chapter 3. In the construction of the GRiST chain graph the conventional way of representing the structure of a chain graph was utilised. This representation entails partitioning the nodes of the graph into subsets known as blocks, with the explanatory nodes in blocks at the right hand and the response nodes on the left and the intermediate nodes in the centre (Bouckaert and Studený, 1995). For the GRiST model this partitioning corresponds to the probability building blocks and in this section the block structures and the construction process are examined. The GRiST chain graph blocks are listed below:

1. Suicide specific nodes.
2. Insight and responsibility.
3. Self neglect appearance.
4. General impaired cognitive function.
5. General depression.
6. General medical therapy.
7. General presentation.
8. General feelings and emotions.
9. General self worth.
10. General personality.
11. General engagement with world.
12. General serious mental illness.
13. General physical health problems.
14. Adverse life events.
15. General demographics.
16. General social context.
17. General current behaviour.
18. General substance misuse.

The nodes within a chain graph block structure are linked together via undirected edges and as such these block structures correspond directly to the Markov random field probability building blocks that some of the GRiST component structures map to. The block structures are then linked together via any nodes within them that are connected. However, whilst the links within blocks are undirected, the links between blocks are directed. In the list of the GRiST chain graph blocks listed above not all of these blocks are ‘conventional’ chain graph block structures. ‘Conventional’ in the sense that not all of them map to Markov random fields but for the construction of the GRiST chain graph given its peculiarities it was found to be convenient to model the blocks in this manner. However, for clarities sake, the following blocks are the ones that model conventional chain graph blocks:

- Insight and responsibility (block 2).
- Self neglect appearance (block 3).
- General impaired cognitive function (block 4).
- General depression (block 5).
- General medical therapy (block 6).

And the non conventional chain graph blocks are:

- General suicide specific nodes (block 1).
- General presentation (block 7).
- Feelings and emotions (block 8).
- Self worth (block 9).
- Personality (block 10).
- Engagement with world (block 11).
- Serious mental illness (block 12).
- Physical health problems (block 13).
- Adverse life events (block 14).
- General demographics (block 15).
- General social context (block 16).
- Current behaviour (block 17).
- General substance misuse (block 18).

These are termed non conventional because they do not map to Markov random fields as they include directed edges, other studies have done extensions to the conventional chain graph model (see Zhang et al, 2011). However, in the GRiST case it is purely a design choice and does not have any effect on the structure and processing of the graph. This is because when it comes to the actual processing of the data, the GRiST block structures that correspond to ‘conventional’ chain block structures are treated as chain block structures and the ones that do not are not treated as composite chain graph structures but rather like different distinct chain block structures containing single nodes. Each chain graph block structure represents a model in its own right whose values are only dependent on the prior and concurrent nodes. The prior nodes in this context refer to nodes in earlier blocks whilst concurrent nodes refer to nodes within the same block. As a direct result of this a lot can be discovered from analysing each block individually and not just within the context of the overall chain graph. The decision to model each of the building blocks individually, helped to reduce some of the complexity inherent in the process, as the converting of the GRiST knowledge structure with its 279 unique nodes into a probabilistic graphical model is not a trivial one. This also aided in the issue of reducing the processing and computational power required for parameter learning and the overall processing of the model. Hence in this section analysis is carried out for some of the blocks that make up the GRiST chain graph.

We will now consider a representative sample of the different types of block structures. The first block listed and to be considered is the *general suicide specific nodes.* This does not fall under the category of the conventional chain graph block structure but for clarity we have used the concept of a block to group these nodes together. The nodes contained within this block are non generic GRiST nodes, this is the only block that falls under this category. The remaining 17 blocks are either conventional representations of a chain graph block (i.e. Markov random fields) or are GRiST component structures that map to directed graphs. The nodes in the general *suicide specific nodes* block are linked together via different GRiST relationship types and have an overall causal influence in the direction of the top risk node (suicide). The nodes within this category include *suicide past attempt*, *suicide plans*, *suicide ideation*, *suicide end of life preparations* and so on. It comprises of both observed (i.e. the datum nodes) and unobserved nodes. Figure 7.1 gives a more detail view of the nodes in this block.

The second GRiST chain graph block is the *insight and responsibility* block. This block is a fixed generic component structure made up of four nodes. From the mapping rules developed in Chapter 5 the probability building block that this maps to is a Markov random field. Figure 7.2 depicts the Markov random field that this block maps to. The three cliques it contains are also highlighted in the figure. In this block, the observed variables are *the*

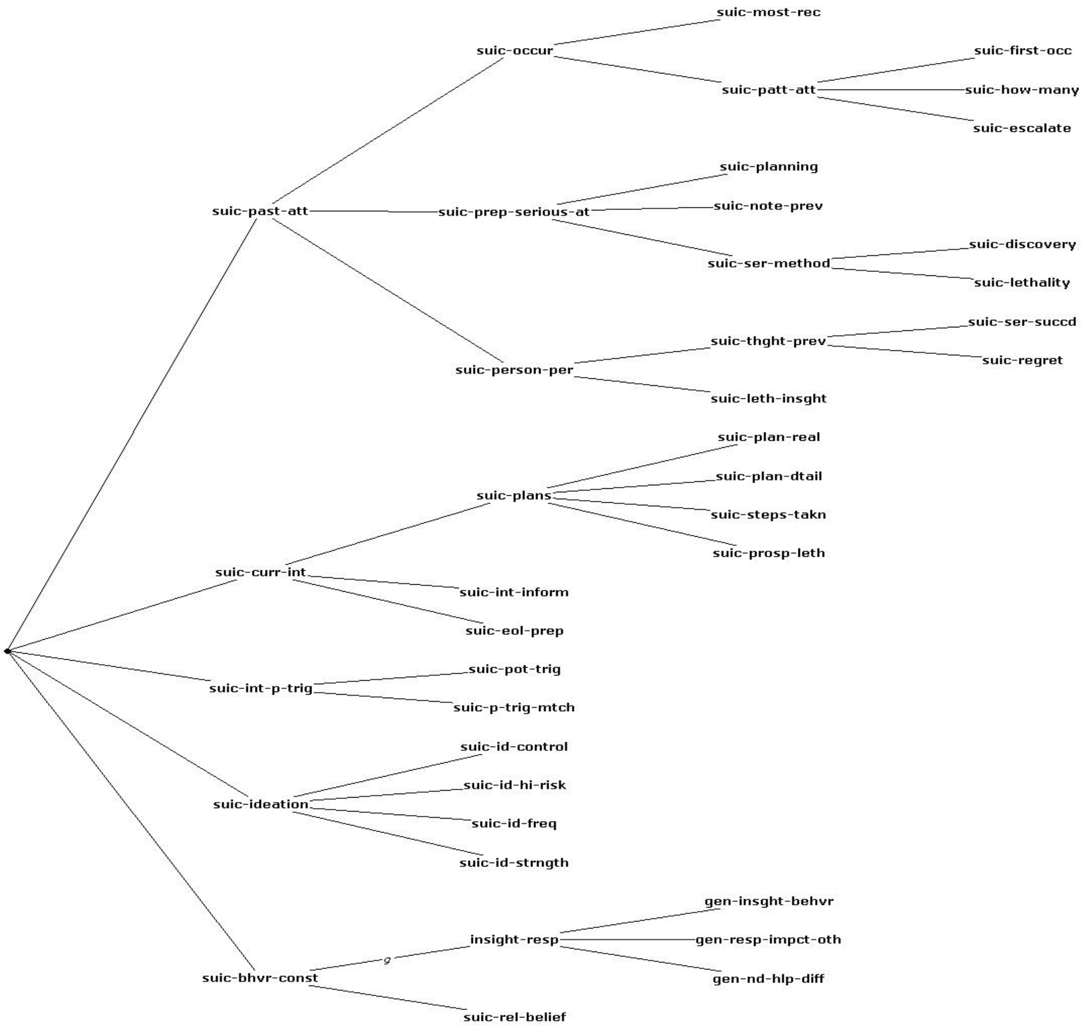


Figure 7.1: Nodes in the first block of the GRiST chain graph block *general suicide specific nodes (g* denotes 'FG' component and unlabelled nodes non-generic components).

insight into behaviour and consequences, *responsibility for impact of behaviour on others* and the *need for help with difficulties* variables whilst the *insight and responsibility* concept node is unobserved. For each of the three cliques in this model the link between each set of variables in each clique is parameterised via the use of potential functions. And from the definition of the joint probability distribution of the random variables of a Markov random field we see that multiplying together the potential functions of all the cliques gives the probability of obtaining a node in a particular setting. These parameters were learned from the GRiST data using the EM algorithm as described in Chapter 6.

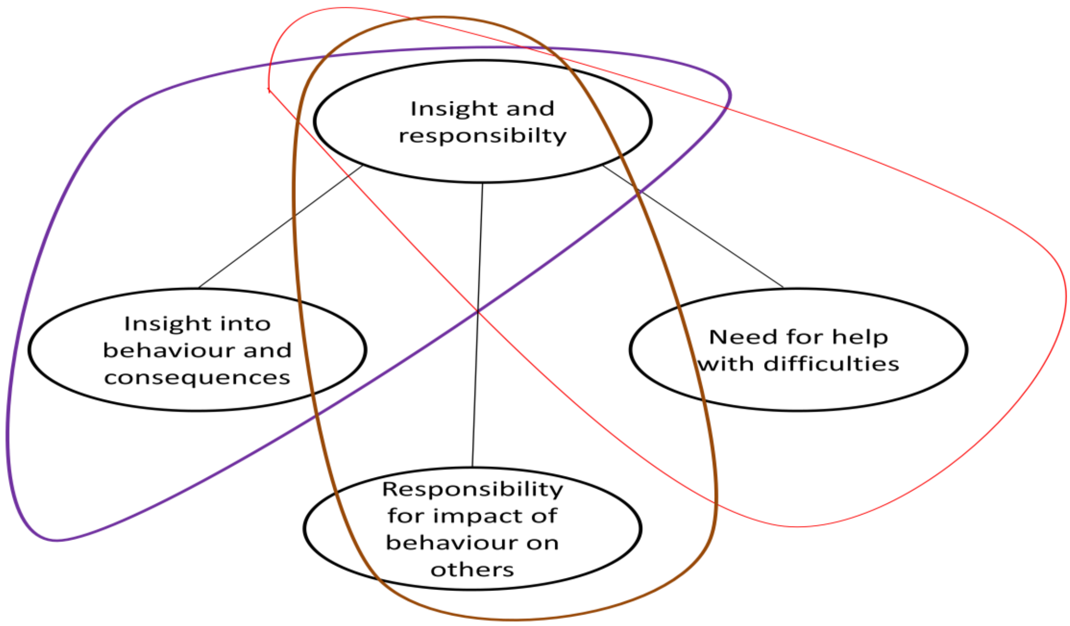


Figure 7.2: The GRiST second chain graph block (a MRF). It has 3 cliques: A) insight and responsibility **and** insight into behaviour and consequences; B) insight and responsibility **and** responsibility for impact of behaviour on others and; C) insight and responsibility **and** need for help with difficulties.

The third GRiST chain graph block is the *self neglect appearance* and this block measures and contributes to the model the impact that an appearance of self neglect contributes to the likelihood of a suicide attempt. Compared to some of the other building blocks such as *general depression* (block 5), the *self neglect appearance* is a simple one containing a total of 5 variables. The *self neglect appearance* has 4 cliques and potential functions over these cliques. Figure 7.3 depicts this chain graph block.

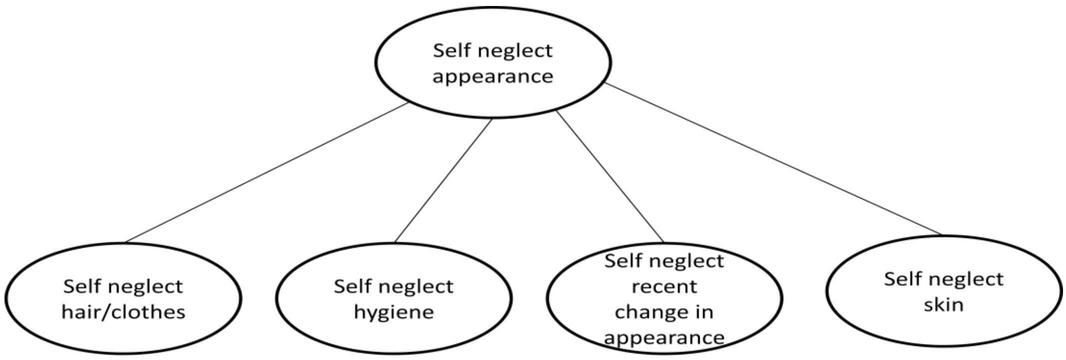


Figure 7.3: GRiST chain graph block 3 – *self neglect appearance.*

The fourth GRiST chain graph block is *general impaired cognitive function* again like the other blocks discussed so far (with the exception of block 1), this is a conventional chain graph block that maps to a Markov random field. It contains a total of three nodes, two of which are observed and one that is unobserved. The fifth building block *depression* is arguably the most interesting and complex of all the GRiST chain graph building blocks. It is made up of 69 nodes, 47 of which are observed and 22 unobserved. Figure 7.4 is a network diagram of depression; it does not show clearly the nodes and their interactions but rather gives a feel for the complexity of the block.

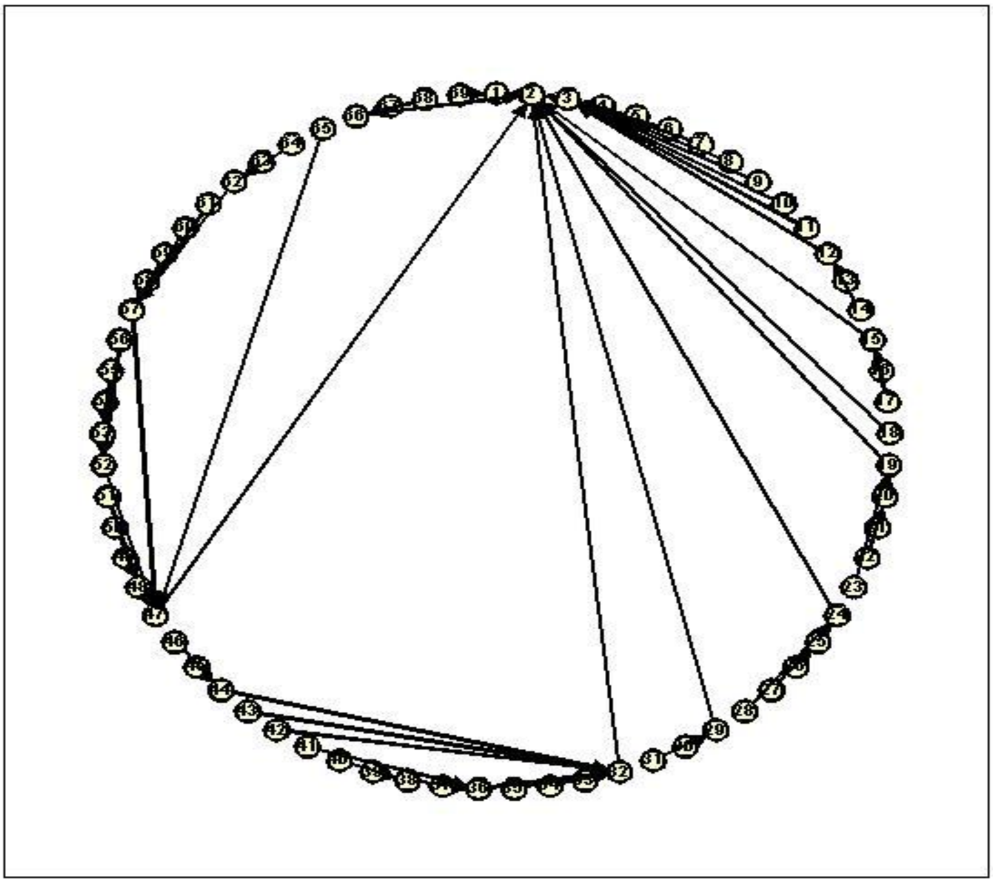


Figure 7.4: Network diagram of the *depression* chain graph block (5).

Figure 7.5 on the other hand depicts clearly the GRiST fixed component structure *depression* and its internal nodes.

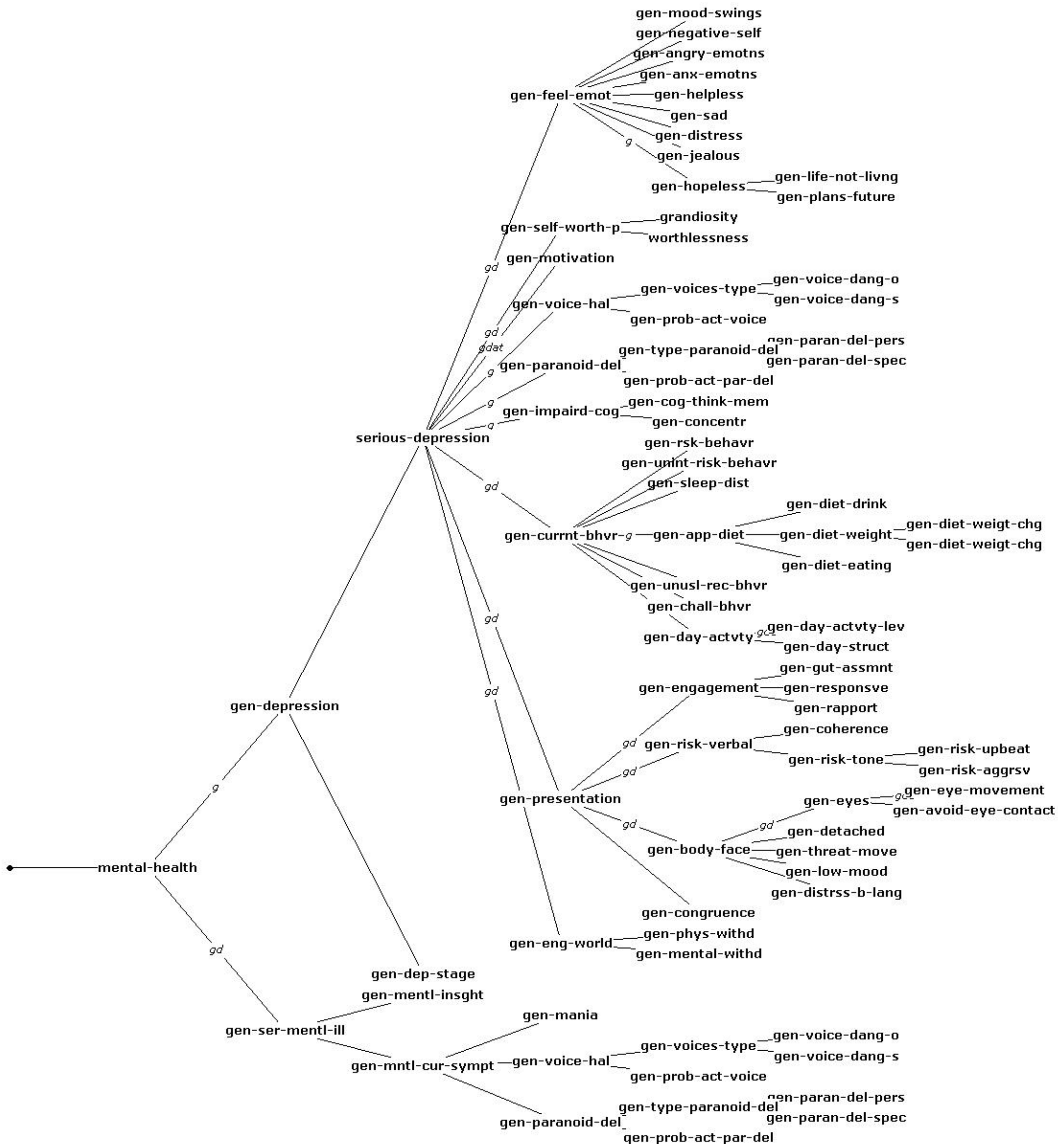


Figure 7.5: The *depression* fixed generic component structure and its internal nodes.

Some of the key features of the mapping rules (Chapter 5) are demonstrated in the *depression* block structure. For instance even though *depression* is itself a high level fixed generic structure it has as internal nodes other generic structures (i.e. both fixed generic and generic distinct structures). Some examples of this can be seen in Figure 7.5, *gen-currnt-bhvr* (general current behaviour) is a generic distinct component structure contained within the fixed generic *depression* structure. However, as a result of the mapping rule that states that for all structures within a high level fixed generic node, the root concept node of the high fixed generic node becomes the relevant context for all its internal nodes the default behaviour of the *gen-currnt-bhvr* is overridden by that of *depression* and the entire high level fixed generic structure maps to a Markov random field. Within the *depression* block, interesting semantic issues are also encountered, for example for the internal fixed generic node *gen-hopeless* (hopelessness) and its internal nodes (*gen-life-not-worth-living* and *gen-plans-for-future*) contained within *depression* (see Figure 7.5). Is it the case that *hopelessness* causes *depression* or does *depression* bring about feelings of *hopelessness*? Markov random fields are precisely good at modelling representations like this where there is a clear association but the direction of causality is not known or does not necessarily exist. Examining the various internal nodes of *depression* it can be seen that there are clear associations but they are not necessarily causal or for some links even if they might be causal, the direction of causality is not obvious. However, what is certain is that the overall contribution from *depression* and its internal nodes act in a direction to influence suicide attempts i.e. for instance, a person with a seriously high level of depression is more likely to attempt suicide than someone who is slightly or not depressed at all. This again illustrates another one of the mapping rules (specifically the external links of a high level FG component structure map to a directed graph). This kind of modelling is precisely what chain graphs make possible and again serve as a further justification for our choice of probabilistic graphical model.

The next GRiST chain building block and the last of the conventional ones is the General medical therapy (block 6) one. This block structure measures the influence of the patient's *concordance with health services/medication/therapies* and has four observed nodes, the *gen-meds-concord* (concordance), *gen-serv-perc-supp* (person's perception of the supportiveness of service received), *gen-serv-last-acc* (time since person accessed services) and the *gen-med-perc-benft* (perceived benefit of medication/therapies). In a similar manner to early block structures discussed this maps to a Markov random field with four cliques.

The next set of block structures to be discussed are the unconventional ones that map to directed graphs. In practice these link to the conventional building blocks and other nodes via their root concept node. The first of these is block 7, which represents the *general presentation* generic distinct component structure. The block structure comprises of 18 nodes and its structure is depicted in Figure 7.6 below.

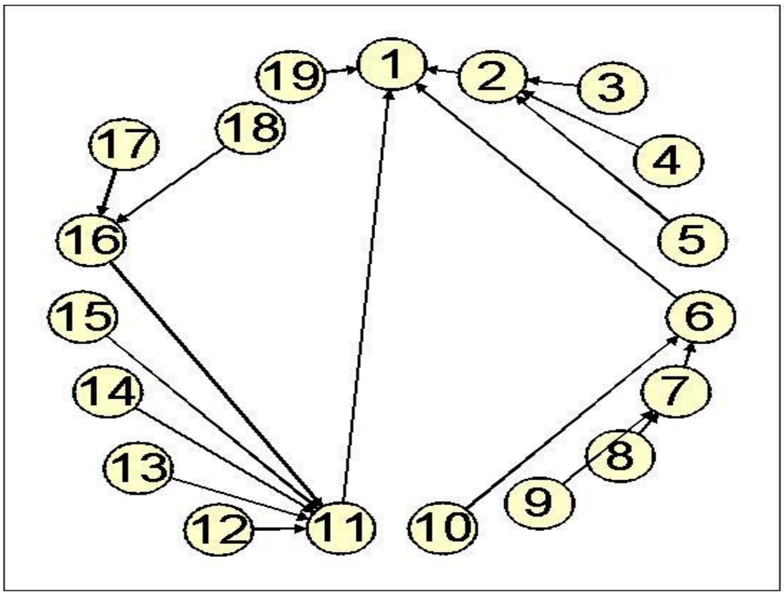


Figure 7.6: Network diagram for the *general presentation* structure.

The nodes in figure 7.6 are numbered in topological order going from the outermost datum node *gen-risk-upbeat* to the root concept node *gen-presentation*. This ordering means that with the nodes numbered 1, 2, 3 and so on, for every edges with (i,j), i < j holds. Table 7.1 lists the corresponding code names and descriptive labels for all the nodes in Figure 7.6.

Table 7.1: Numbers, nodes and descriptions for Figure 7.6

Node Number	Node Code	Description
19	Gen-risk-upbeat	how upbeat or downbeat/depressed
18	Gen-risk-aggrsv	degree of aggression/hostility
17	Gen-risk-tone	Tone
16	Gen-coherence	degree to which the person is making sense
15	Gen-risk-verbal	verbal indicators of risk
14	Gen-gut-assment	assessor's uneasiness about the person
13	Gen-responsve	person's responsiveness
12	Gen-rapport	rapport/empathy
11	Gen-engagement	person's engagement with assessor
10	Gen-eye-movement	eye movement
9	Gen-avoid-eye-contact	avoid eye contact

8	Gen-eyes	Eyes
7	Gen-detached	preoccupied/detached demeanour
6	Gen-threat-move	aggressive/threatening movements, posture, or expression
5	Gen-low-mood	movements, posture, facial expression indicating low mood
4	Gen-distrss-b-lang	body language indicating distress
3	Gen-body-face	body language and expression
2	Gen-congruence	congruence of physical, verbal, and emotional presentation
1	Gen-presentation	person's behavioural presentation during assessment

The block diagrams that map to directed graphs are different from those that map to Markov random fields primarily as a result of the differences in the representations of conditional independencies for both graphs. It is easier to read off the conditional independencies encapsulated in a Markov random field than it is for a directed graph. For a Markov random field as seen in Chapter 3, a variable is conditionally independent of another variable given all its neighbouring nodes. However, for directed graphs the concept of d-separation is used to determine the conditional independencies (see Chapter 3). For the GRiST chain graph block components that map to directed graphs the direction of causality is clear, always going from cause to effect hierarchically up the structure in the direction of the top risk (e.g. suicide). The other blocks such as the feelings and emotions, self worth, personality, serious mental illness and so on, are clearly components that influence suicide risk. In the analysis section the results obtained are analysed to measure the effect of these different factors on the suicide risk assessments obtained from the model.

In the next section the parameter learning process is discussed. The technical details will be omitted as these were covered in Chapter 6.

7.2 Parameter Learning

In this chapter we carry out analysis of independent correlations and on the overall graph versus the expert judgements. For the learning process the results obtained (i.e. the parameters learned), represent the conditional probability distribution of the relevant node, whilst from the factor graph inference the result obtained is the marginal probability of the suicide risk. This marginal probability is then compared with the expert judgements and this acts as a test of how well the factor graph correlates with the expert judgements.

The learning of parameters was carried out as discussed in Chapter 6 using the EM algorithm and in this section we illustrate the process and results from the process by focusing on some subsections of the GRiST chain graph. Parameter learning is extremely important because without knowing the values of these parameters, inference cannot be carried out on the overall model and this in turn means that the model will not be able to make risk assessments.

Two examples component structures will now be discussed for illustrative purposes. The examples to be considered are the *general personality* (block 10) component structure (discussed in this section and on page 171) and the *self worth* (block 9) component structure (discussed on page 166). This initial analysis of the parameter learning of the contribution of single standalone components was done to explore the strength of the contribution that a single component structure will have on the top risk independently from the other component structures. In fact, any of the component structures could have been chosen for this analysis. Later on in the chapter (page 179) we consider the full graphical structure (with the contributions from all the component structures). The *general personality* structure is made up of nine nodes, eight of which are observed. It is a generic distinct GRiST component structure and has the causal relation *contributes_to* linking its nodes together. Figure 7.7 depicts the adjacency matrix used to represent the model in the pmtk3 and bnet toolkits for MATLAB.

The parameter learning process involved using the 9417 GRiST data cases in the EM algorithm. The data were split into two sets, 2000 cases were used as the test data and the remaining 7417 were used for training. The algorithm ran over a few iterations until the parameters converged into a final set of values which represent the best fit. The pre set maximum number of iterations that were set was ten. However, for this block structure the parameters converged into the final set of values after three iterations of the algorithm.

In the learning process all datum nodes were treated as observed nodes (i.e. nodes whose values are known) and the concept nodes as unobserved nodes (i.e. nodes whose values are not directly observed). In this particular example there is one unobserved node i.e. the component structure's root node *gen-personality* and eight observed nodes (namely *gen-assertive*, *gen-empathy-abil*, *gen-dependence*, *gen-controlling*, *gen-coping-abil*, *gen-hostile*, *gen-impulse* and finally *gen-reliable*).

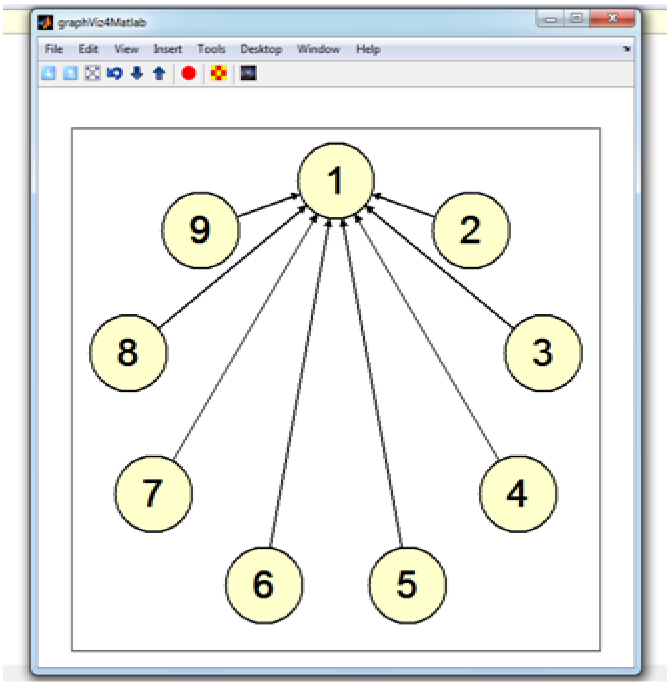


Figure 7.7: Figure depicting the *gen-personality* GD component structure. In the graph node **1** represents *gen-personality*, **2** *gen-assertive*, **3** *gen-empathy-abil*, **4** *gen-dependence*, **5** *gen-controlling*, **6** *gen-coping-abil*, **7** *gen-hostile*, **8** *gen-impulse* and finally **9** *gen-reliable*.

The parameters learned from the data were as expected directly correlated to the number of occurrences of the different values in the dataset.

On completion of the parameter learning process for the different chain graph block structures the next step in the process was the conversion to a factor graph to facilitate the use of the factor graph sum product algorithm. A similar process to the above for *gen-personality* was carried out to learn the parameters using the EM algorithm for all the block structures. As mentioned in Chapter 6, the EM algorithm was used for parameter learning for both directed and undirected graphs.

7.2.1 Parameter Learning Results and Analysis

In this section some of the results obtained from the parameter learning are analysed and discussed. We start by examining the parameters learned from the data for the ninth building block of GRiST chain graph i.e. *person's perspective of self worth* (gen-self-worth-p) block.

7.2.1.1 Self Worth

This structure is made up of three nodes (two observed nodes and an unobserved root node). For the purposes of this discussion, the observed nodes *grandiosity* and *worthlessness* are assigned numbers 2 and 3 respectively, whilst the unobserved root concept *general self worth* is assigned the number 1. Each of these nodes can have ten possible states and so the process of parameter learning return results for each of the possible states. On completion of the learning process the following results were obtained for the probability distributions of nodes 2 and 3.

Table 7.2: Parameters learned from data for GRiST chain block structure *general self worth*

Possible states for Node 1

Possible State	**Node 3 (Worthlessness)**	**Node 2 (Grandiosity)**
1	0.0758	0.9566
2	0.0489	0.0183
3	0.0679	0.0086
4	0.0585	0.0047
5	0.3152	0.0047
6	0.1943	0.0024
7	0.0237	0.0029
8	0.2014	0.0014
9	0.0071	0.0003
10	0.0072	0.0002

Plotting the distributions for *worthlessness* and *grandiosity,* against their possible states give Figures 7.8 and 7.9 respectively.

From Figure 7.8 it can be seen that the states with the highest probabilities of occurring are the middle range states (i.e. between 4 and 7), followed by the slightly higher state 8, the lower states between 1, 4 and 7 are less likely to occur and the highest states 9 and 10 are the very least likely to occur.

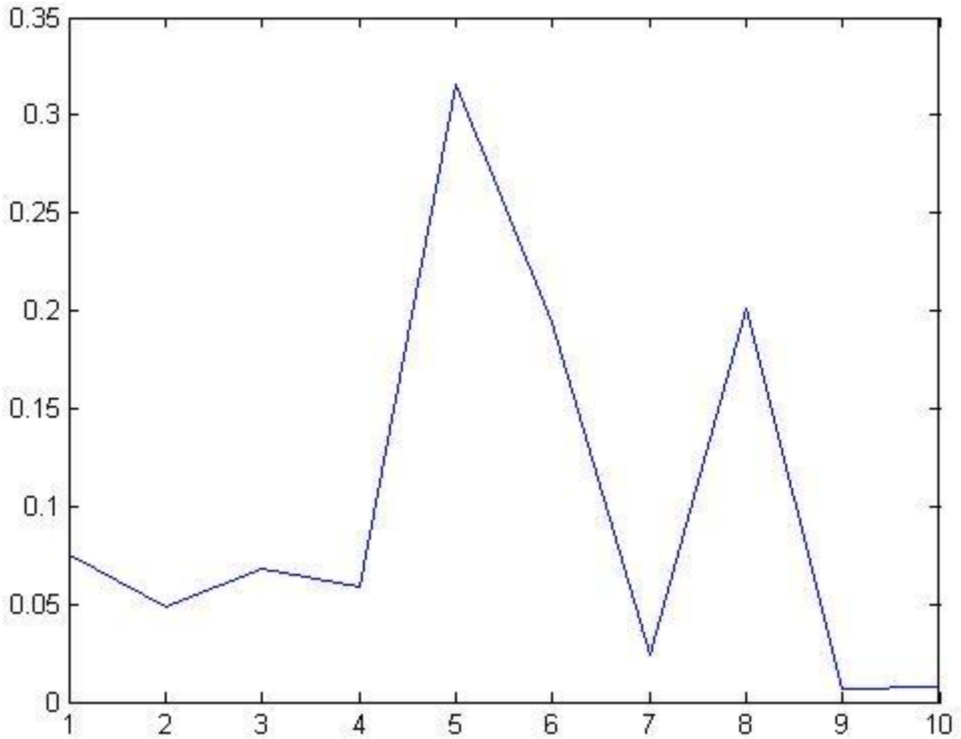


Figure 7.8: Probability distribution of node 3 (*worthlessness*).

On the other hand the probability distribution for *grandiosity* is very different from its sibling node *worthlessness.* From Figure 7.9, it can be seen that for the probability distribution of *grandiosity*, the highest probability distributions map to the very lowest states whilst the middle range to the highest states have very low probability distribution values mapped to them. Figures 7.8 and 7.9 help to identify the values of the nodes that give the highest and lowest contribution to the overall sense of *self worth* of the patient.

For node 1 (self worth)

For the unobserved node 1, the conditional probability distribution obtained consists of all the possible probability distributions of node 1, given all the possible values of nodes 2 and 3. This means that for the ten possible states of each of nodes 2 and 3, a row of possible values is obtained for node 1. A snapshot of these results are displayed in a compact form in Table 7.3. In Table 7.3, the values to the left of the colon represent the values of nodes 3 and 2 respectively, whist the values to the right of the colon represent the values learned from data for node 1.

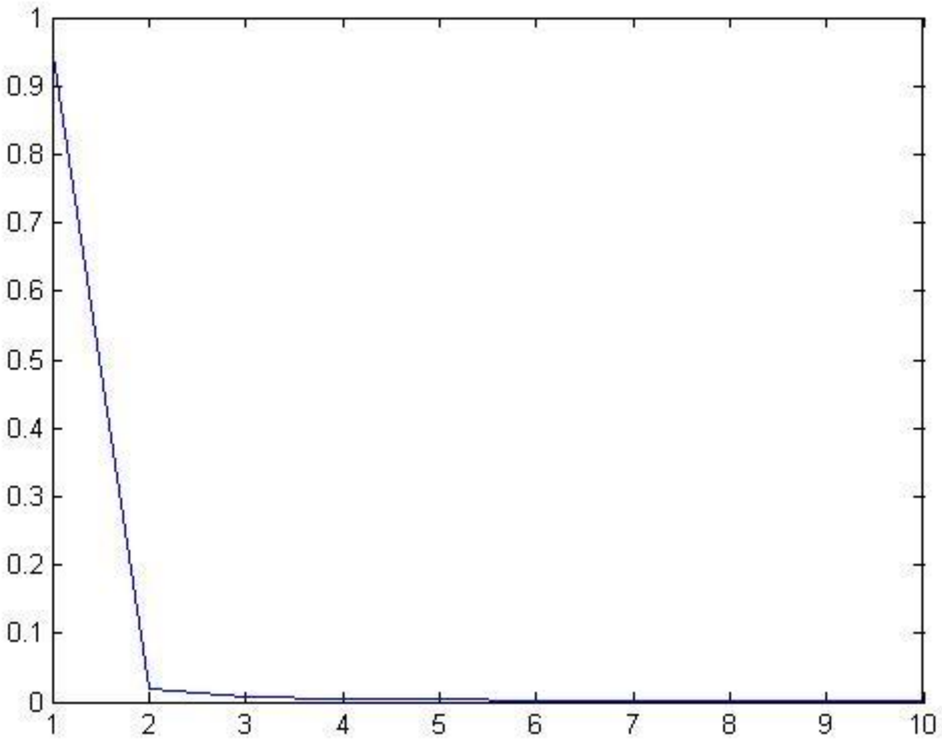


Figure 7.9: Probability distribution of node 2 (*grandiosity*).

Table 7.3: Subset of conditional probability distribution of self worth

1 1 :	0.8358	0.0095	0.0161	0.0343	0.0375	0.0173	0.0205	0.0189	0.0088	0.0014
2 1 :	0.0880	0.0017	0.0802	0.1585	0.2028	0.1941	0.2224	0.0441	0.0081	0.0000
9 1 :	0.0000	0.0000	0.0000	0.5567	0.0000	0.0000	0.0000	0.0000	0.4433	0.0000
10 1 :	0.3582	0.0000	0.0000	0.6418	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1 2 :	0.7689	0.0152	0.0168	0.0446	0.0475	0.0450	0.0401	0.0035	0.0154	0.0031
2 2 :	0.1199	0.0914	0.0147	0.0231	0.0928	0.0490	0.3839	0.1463	0.0790	0.0000
8 2 :	0.5150	0.0000	0.1670	0.0000	0.0731	0.0000	0.0137	0.2313	0.0000	0.0000
9 2 :	0.0000	0.0000	0.0000	0.2929	0.0000	0.0000	0.0000	0.0000	0.7071	0.0000
10 2 :	0.4228	0.0000	0.0000	0.5772	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1 3 :	0.7556	0.0049	0.0106	0.0419	0.0261	0.0155	0.0890	0.0226	0.0324	0.0014
6 3 :	0.1126	0.0560	0.1603	0.0342	0.0000	0.5316	0.0710	0.0343	0.0000	0.0000
• • •										

7.2.2 Probabilistic Contributions

Using the bnet toolbox inference engine, the probabilistic contributions to the final value of the top risk for the different block structures were obtained. This probabilistic contribution represents the probability distribution of the variable of interest averaging over the other nodes in the block structure and was computed to facilitate the probability of particular nodes given certain evidence. Using the inference engine, the contribution of the root node *gen-self-worth* of the GRiST chain graph ninth block structure was obtained. The process of marginalisation involves the addition of specified evidence into the network. Here the split data cases comes into play where the first 2000 cases designated the test cases are passed as the required evidence for marginalisation and the remaining 7417 cases are used for the initial training of the structures parameters. In Figure 7.10 the probabilistic contribution of the *gen-self-worth* is plotted against the corresponding experts risk judgements for suicide. This serves to give a feel for the relationship between *general self worth* and *suicide risk*. In a similar manner the contributions obtained from other blocks are compared to the expert risk judgement. This aids in the identification of relationships and strength of relationships between the various nodes and suicide risk. However, the acid test still remains the comparison that will be done later between the marginal probability distribution obtained for suicide risk using the GRiST factor graph inference algorithm and the experts risk judgements. Figure 7.10 is a plot of *general self worth's* probabilistic contribution against the domain experts' judgements (using the first 2000 cases).

In the plot of the contribution of *gen-self-worth* vs *expert judgements* in Figure 7.10 (which only considers this subgraph) although a slight trend can be seen, it is very slight. However, this is not totally unexpected for two main reasons:

- The first is that only a very small subsection of contributing factors of the entire GRiST knowledge structure to suicide risk has been taken into account and
- Secondly the vast majority of the training data (7417 of 9417) was used for the training of the model parameters, whilst the remaining 2000 cases (i.e. the test data) were introduced as evidence during the marginalisation process (compare this with Figure 7.11, where 7417 cases were entered as evidence). In Figure 7.11 where more data cases are used, the shape depicting the relationship between the set of values becomes more distinct than in Figure 7.10 (where 2000 cases was used as evidence) but this does not necessarily imply better results due to the presence of outliers in Figure 7.11.

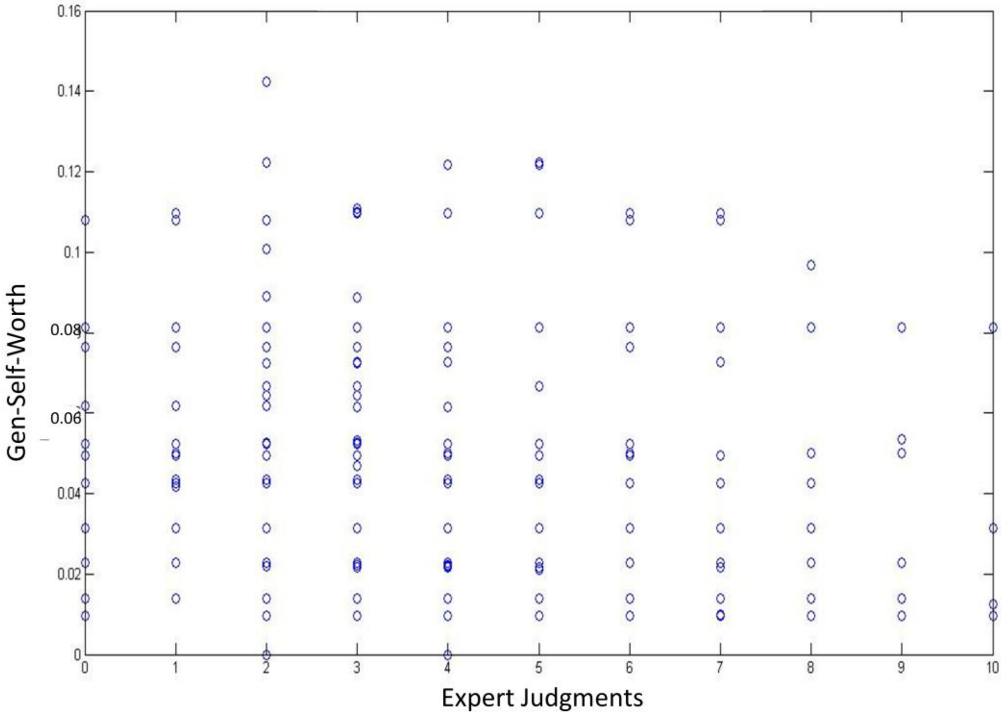


Figure 7.10: Contributions of *gen-self-worth* vs *expert judgements taken from GRiST* (evidence = 2000 data cases).

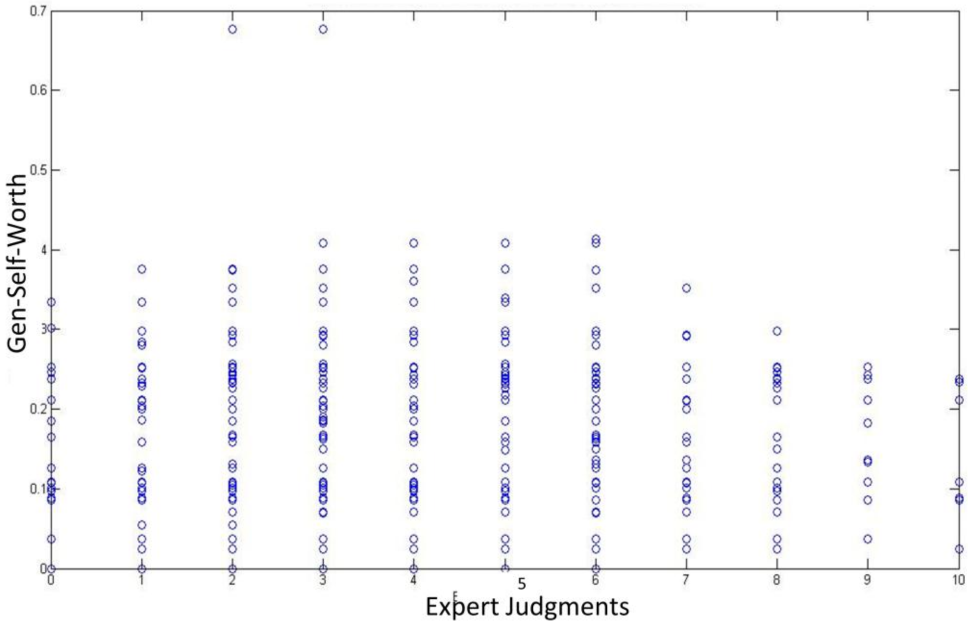


Figure 7.11: Contribution of *gen-self-worth* vs *expert judgements* (evidence = 7419 data cases).

The expected result was that the more factors (i.e. variables and block structures) are taken into account doing the inference process, the closer the final value will be to the experts' judgements, to assess this we continue with the analysis of the subgraphs and their contributions.

7.2.2.1 General Personality

Next another example of the parameter learning results for a GRiST chain graph block structure (the tenth) is considered. This is the *gen-personality* block structure and is made up of nine nodes. Earlier on in the chapter it was seen that for the *gen-personality* block structure the best fit was obtained after three iterations. This node holds one of five possible states (i.e. states 1 to 5).

The conditional probability distributions obtained from the parameter learning for the observed nodes of the *gen-personality* block structure are as follows:

Node 9: *gen-assertive*, Node 8: *gen-empathy-abil*, Node 7: *gen-dependence*, Node 6: *gen-cotrolling*, Node 5: *gen-coping-abil*, Node 4: *gen-hostile*, Node 3: *gen-impulse*, Node 2: *gen-reliable* and Node 1: *gen-personality*

Table 7.4: Learned parameters for *gen-probability* block structure observed nodes

States	**Node 9**	**Node 8**	**Node 7**	**Node 6**	**Node 5**	**Node 4**	**Node 3**	**Node 2**
1	0.3118	0.8680	0.7643	0.8797	0.7172	0.9339	0.7917	0.8350
2	0.2261	0.0560	0.0808	0.0680	0.0537	0.0000	0.0716	0.0693
3	0.2556	0.0411	0.0760	0.0327	0.1014	0.0532	0.0735	0.0513
4	0.1156	0.0295	0.0640	0.0154	0.1073	0.0000	0.0502	0.0346
5	0.0910	0.0054	0.0149	0.0042	0.0204	0.0128	0.0131	0.0098

The probability distribution graphs of these nodes 2 to 9 are depicted in Figure 7.12

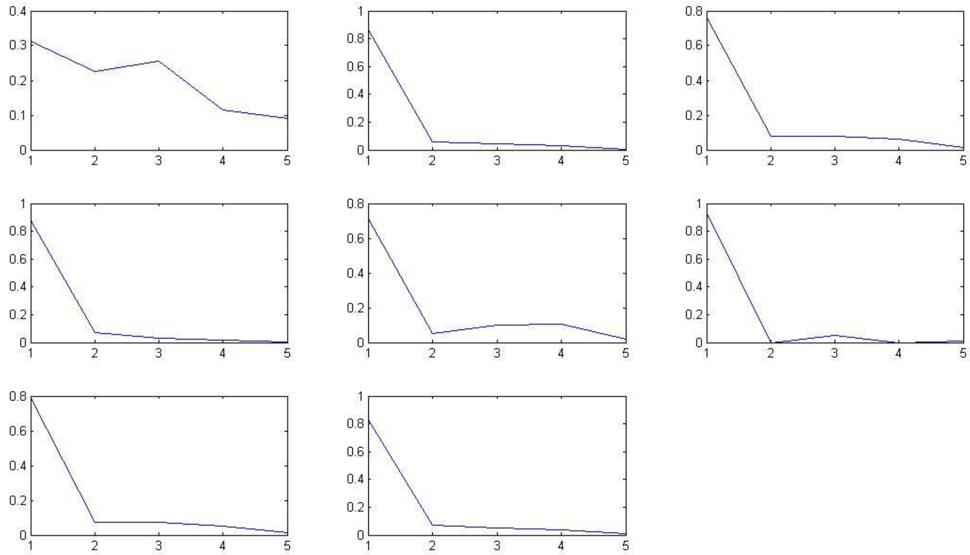


Figure 7.12: Probability distribution of the 8 observed nodes of the *gen-personality* structure, with the probability distributions depicted along the y-axis and their possible states along the x-axis (going from top left to right, for nodes 9 all the way down to node 2).

Examining the probability distributions of the eight observed nodes, the similarities that exist in the probability distribution of all the nodes with the exception of node 9 (*gen-assertive)* can be seen, this depicts the fact that extreme values are less likely. In the seven similar distributions, the probability distribution values are at their peak with the lowest state value and then decrease and remain relatively low into the mid and high ranges.

The probability distribution for the root concept *gen-personality* (node 1) is a complex one, as it contains values for every possible state and combination of states of the observed nodes (390,562 rows in total). However, an interesting fact from the parameters learned for the root node is that for its probability distribution, the highest probability values are seen when nodes 2 to 8 are in their lowest ranges and for these values node 9 does not yield much influence in comparison to the collective influence of its 'united' sibling nodes. In addition to this it was also observed that unlike the earlier block discussed (i.e. *person's perspective of self worth)* the *gen-personality* returned a large number of values with probability values of zero.

This phenomenon can be explained by examining the probability distribution of the observed nodes for the *person's perspective of self worth;* the probability distribution of its observed nodes are fairly spread out (see Figures 7.8 and 7.9), whilst for the *gen-personality* structure this is not the case (see Figure 7.12). The effect this has is that in the areas such as states 1 where the probability distribution is high, there is a correspondingly high probability distribution in the root node but in the other states where the values are low and tending to zero; this has a corresponding effect on the root concept node *gen-personality* (node 1). Some examples of this can be seen in Table 7.5. In Table 7.5, the values to the left of the colon represent the values of nodes 9, 8, 7, 6, 5, 4, 3 and 2 respectively, whilst the values to the right of the colon represent the values learned from data for node 1.

Table 7.5: Snapshot of learned conditional probability distribution for the *gen-personality* variable. The first eight values before the colon, represent the possible states of its internal nodes and the five values after the colon its conditional probability distribution.

```
1 1 1 1 1 1 1 1 : 0.9991 0.0009 0.0000 0.0000 0.0000
2 1 1 1 1 1 1 1 : 0.8745 0.0000 0.0000 0.0000 0.1255
3 1 1 1 1 1 1 1 : 0.6136 0.3864 0.0000 0.0000 0.0000
4 1 1 1 1 1 1 1 : 0.0000 1.0000 0.0000 0.0000 0.0000
5 1 1 1 1 1 1 1 : 1.0000 0.0000 0.0000 0.0000 0.0000
1 2 1 1 1 1 1 1 : 0.5501 0.2319 0.0000 0.0000 0.2179
2 3 1 1 1 1 1 1 : 0.9139 0.0000 0.0000 0.0000 0.0861
1 4 1 1 1 1 1 1 : 0.2740 0.5880 0.0000 0.0000 0.1380
2 4 1 1 1 1 1 1 : 0.0000 0.0000 0.0000 0.0000 0.0000
2 5 1 1 1 1 1 1 : 0.0000 0.0000 0.0000 0.0000 0.0000
3 5 1 1 1 1 1 1 : 0.9358 0.0642 0.0000 0.0000 0.0000
4 5 1 1 1 1 1 1 : 0.0000 0.0000 0.0000 0.0000 0.0000
5 5 1 1 1 1 1 1 : 0.0000 0.0000 0.0000 0.0000 0.0000
. . .
```

The parameters for all the block structures are obtained in a similar manner to the above.

7.2.3 Conversion to Factor Graph

Having obtained the parameters for the various chain graph blocks, the next step in the process is the conversion from the chain graph to the factor graph. The rationale behind this conversion is to make it possible for the effective sum product algorithm to be used on the factor graph for the risk assessments. This algorithm cannot be used on chain graphs. For the actual conversion two methods were considered, firstly the process outlined in Chapter 6 to convert from the hybrid of the probability building blocks (essentially the chain graph) or alternatively both of the toolboxes that were used for the portion of the developments done using MATLAB (i.e. bnet and pmtk3). Both have functions that facilitate the conversion from directed graphs and Markov random fields to factor graphs. In the pmtk3 toolbox the functions are:

fg = dgmToFactorGraph(dgm) and fg = mrfToFactorGraph(mrf) respectively.

For the bnet toolbox the function to convert from Bayesian network to factor graph is

fg = bnet_to_fgraph(bnet)

The conversion from directed graph to factor graph via the toolbox functions follows a similar pattern to that of Chapter 6, it is briefly outlined here for completeness. For the bnet toolbox, the bnet_to_fgraph takes in as input the Bayesian network to be converted into a factor graph and from the Bayesian networks converts to the required factor graph. The pmtk3 toolbox directed graphical model to factor graph dgmToFactorGraph also operates in a similar manner. It takes as input the directed graph, converts it into a Markov random field and then converts the Markov random field into a factor graph with its constituent nodes and factors. The mapping rules and the process leading to the generating of the right format of input graphs have been discussed in the preceding chapters. What this means is that the MATLAB toolkits are not making any design decisions but processing as instructed to via the written scripts.

Having learned the GRiST chain graph parameters from the data and converted the chain graph into its corresponding factor graph representation, inference was carried out on the factor graph to produce marginal probability distributions that are used as the basis for comparison with the expert judgements for the evaluation of the model. The next section considers the analysis of the results.

7.2.4 Analysis of Results

The next step in the process was now the computing of the probabilistic contributions to the overall top risk. These contributions are what represent the risk prediction and to evaluate the results, they will be compared with the expert risk judgements. In this section the analysis of the results are done via comparisons of the contributions of individual subgraphs against the expert judgement values. We start off by comparing the contributions of some of the subgraphs to the expert judgements and then build up to the comparison of the factor graph marginal probability distribution for suicide with the expert judgements.

7.2.4.1 General impaired cognitive function (gen-impaird-cog) Chain Graph Block Structure

The contribution of this block was compared and plotted against the expert judgements, the results (Figure 7.13) show some correlation but not as defined as that of *gen-self-worth* (in Figure 7.11).

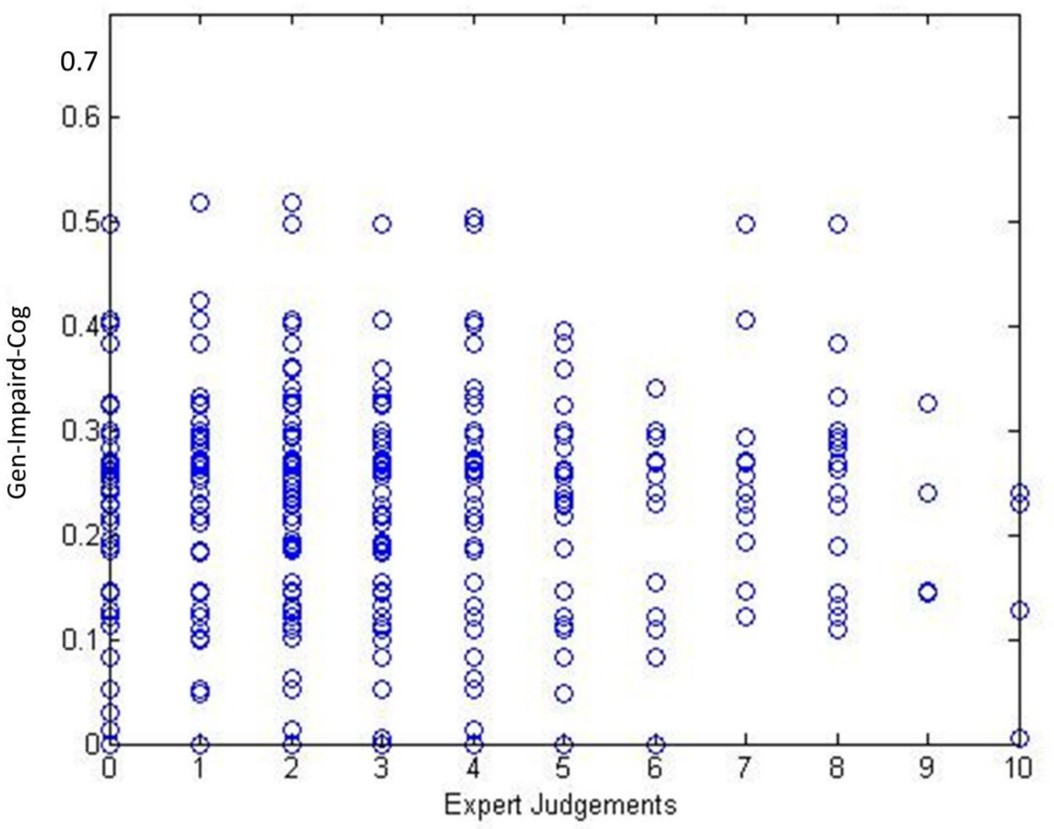


Figure 7.13: Contribution of *gen-impaird-cog* vs *expert judgements.*

Some other statistics were obtained to aid the comparisons of the marginal probability distribution of this block via the experts judgements. These include:

The correlation coefficient which helps to establish the presence or absence of statistically significant correlations between sets of data. On applying it to the gen-impaired-cog data and the experts judgement the following results were obtained.

The correlations R returned:

R =

1.0000	0.0274
0.0274	1.0000

Whilst the p-value P returned was:

P =

1.0000	0.0071
0.0071	1.0000

From the values above the correlation between the *gen-impaired-cog* block structure and the expert judgements is not zero. However, the correlation is very small but then this is as expected as these values were obtained by considering a small section of the entire GRiST structure.

7.2.4.2 General Engagement with World (gen-eng-world) Chain Graph Block Structure

In a similar manner to the *gen-impaired-cog* block structure above, the contribution of the *gen-eng-world* block structure was compared against the expert judgements. Figure 7.14 depicts the plot of the two sets of data.

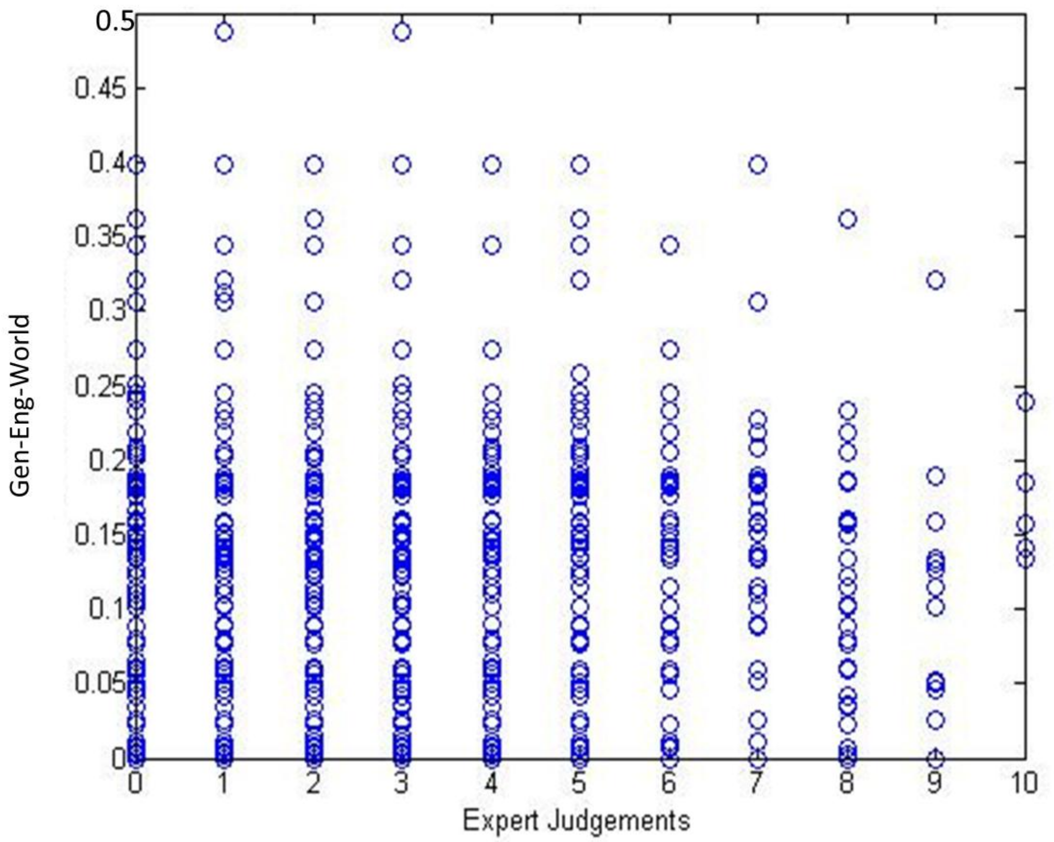


Figure 7.14: Contribution of *gen-eng-world* vs *expert judgements* (evidence = 100 data cases).

It can immediately be seen that like in the other plots obtained so far of block structure contributions against the expert judgements the greatest amount of correlation is for contributions under 0.25, the concentration of overlap in this range spread across the expert judgements (between the expert judgement values of 0 to 9) is more concentrated than in previous graphs seen. However it also has the more scattered data outside this region than the other graphs examined so far. This means that for the *gen-eng-world* distribution the probability of obtaining the different expert judgement values is not widely different. The correlation coefficient was also obtained for these sets of data to confirm whether or not a significant correlation exists between them.

The correlation R was

R =

1.0000 0.0318

0.0318 1.0000

And the p-value P:

1.0000 0.0000

0.0000 1.0000

Again like in the case of the *gen-impaird-cog* the results imply that there is correlation between the two sets but this correlation is significant at a very low value.

7.2.4.3 Insight Responsibility (insight-resp) Chain Graph Block Structure

Figure 7.15, depicts the plot of *insight-resp's* contribution against the expert judgements. Again even though this graph is different in its own right from the other graphs, it can be seen that all the graphs share a generally similar form.

From the similar form that the different contributions vs the expert judgements share and based on the statistical significance established for them, none of the subgraphs on its own has had a high correlation to the expert judgements when considering its individual contribution. This is not unexpected as each subgraph on its own represents a very small part of the overall GRiST structure. Next we consider the the entire GRiST chain graph and its correlation to the expert judgements.

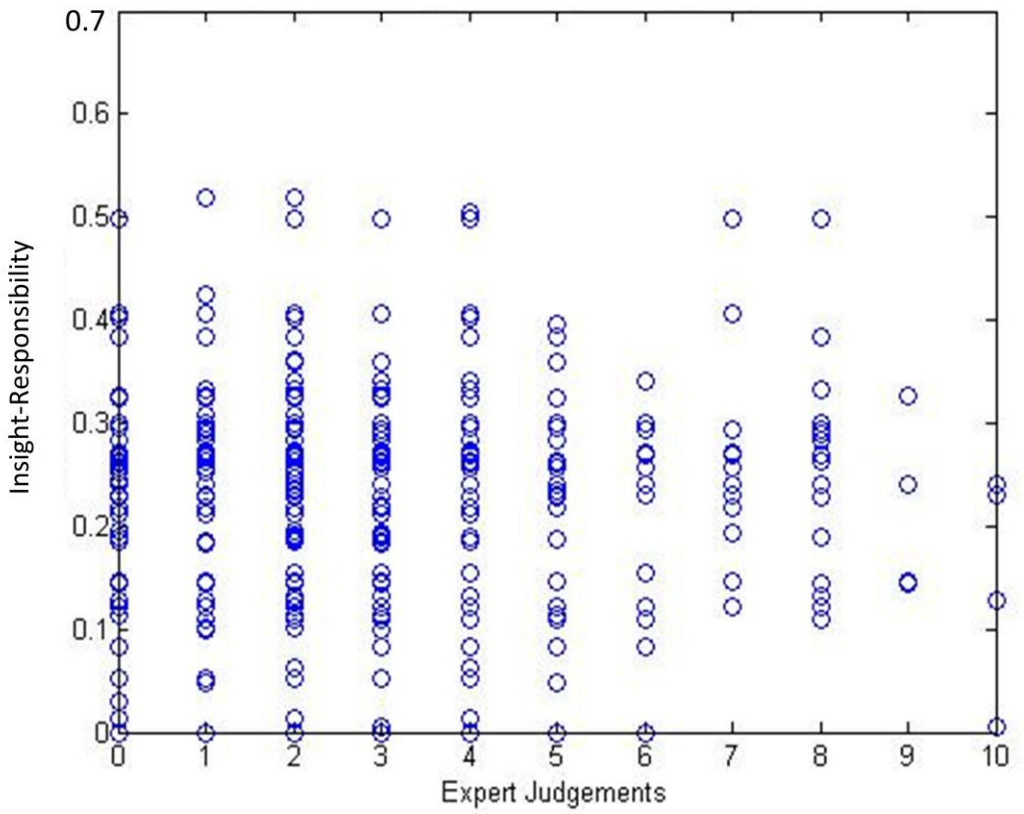


Figure 7.15: Contribution of *insight-responsibility* vs *expert judgements.*

7.3 GRiST Factor Graph Results Comparison with Expert Judgements

In a similar manner to the processes for the subgraphs discussed in the preceding sections, when the sum-product algorithm is applied to the GRiST factor graph, it results in the values of the probability distribution of the top risk (i.e. suicide) being obtained. To measure the correlation between the results of the factor graph and the expert judgements as was done for the subgraphs, the two sets of data were compared. The probability distribution of the suicide node was also converted into discrete integers. Analyses of these two datasets showed correlation between the two sets and they were then plotted against each other (see Figure 7.16).

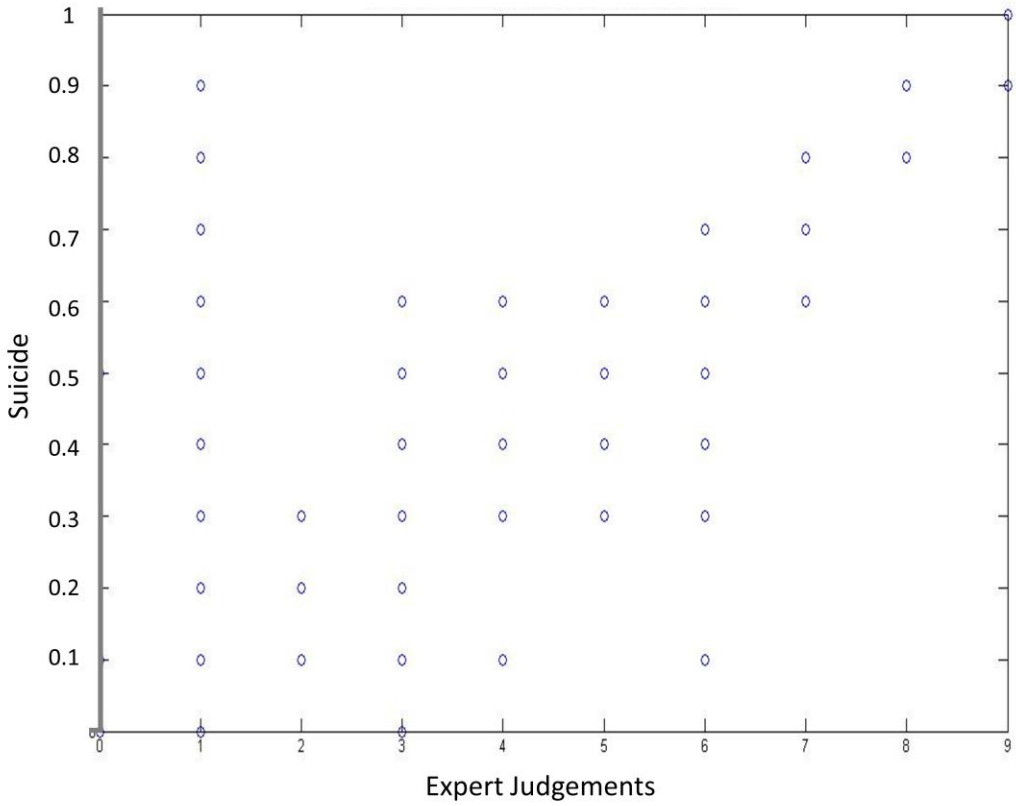


Figure 7.16: Factor graph *suicide vs expert judgements.*

From Figure 7.16 we can see some indication of a trend for correlation between the suicide marginal probability distribution and the expert judgements for values 0 and 2 to 9. However, due to unknown reasons no correlation is present for value 1. As mentioned previously in the chapter the more subgraphs were added the better the correlation obtained and this was also seen to be the case when contrasted with inference on a model of GRiST with a fully directed representation (as against the more accurate chain graph representation containing both directed and undirected edges). In the next section we discuss some further results obtained from the implemented GRiST probabilistic graphical model.

7.4 GRiST Factor Graph Further Analysis of Results

In addition to the previously discussed tests, the GRiST factor graph was also applied to an additional 22,845 GRiST data cases. The results obtained from this are discussed in this section.

After running the sum-product algorithm a series of results were obtained giving the marginal probability distributions of the variables. The final suicide marginal distribution was then produced and compared with the weighted average obtained from the expert judgements. The weighted averages were obtained using the following equation:

$$weighted\ average\ of\ sample\ with\ value\ x = \frac{weight\ of\ samples\ with\ value\ x}{total\ weight\ of\ samples}.$$

The results obtained using the above equation are shown in table 7.6.

Table 7.6: GRiST expert judgements weighted averages

Expert Judgement Values	**Weighted Averages**
0	0.089343
1	0.201937
2	0.247255
3	0.204090
4	0.093218
5	0.073842
6	0.033261
7	0.027771
8	0.019590
9	0.007319
10	0.002368

7.4.1 Analysis of Patient Level Data Results

To establish how the ratings are linked to specific patients, the factor graph algorithm was run on patient level data. This process and the results obtained are discussed below.

The different possible results that can be obtained from the algorithms and the expert judgements were grouped into the following categories:

- Low – This refers to resultant values of 1, 2, or 3 (in the case of expert judgements, this will refer to patient cases that the experts have categorised as having suicide risks of 1, 2, 3).

- Medium – in a similar fashion to low, these refer to all those with values 4, 5 or 6.
- High – finally these refer to all those with values 7, 8, 9 or 10.

The results obtained are summarised below and followed by a discussion of the results:

Table 7.7: Expert judgements weighted averages based on categories

Category	Weighted Average	Percentage (of Low, Medium & High)
Low	0.7172446	71.7%
Medium	0.220026039	22.0%
High	0.0627293171	6.3%

Table 7.7 gives the GRiST expert judgements weighted averages based on the grouped categories (i.e. low, medium and high) whereas table 7.6 gave the weighted average based on the possible risk levels ranging from 0 to 10.

Table 7.8: Factor graph results based on categories

LOW	**Non-Normalised**	**Normalised**
Low	0.154839	0.53063763
Medium	0.107753	0.3692726
High	0.029206	0.1000898
MEDIUM		
Low	0.249445	0.20511225
Medium	0.706861	0.58123372
High	0.259833	0.21365403
HIGH		
Low	0.177838	0.08256439
Medium	0.435318	0.20210397
High	1.540775	0.71533164

Table 7.8 gives the results obtained for the three different categories using the GRiST probabilistic graphical model. In tables 7.9 and 7.10, the results depicted in tables 7.8 are then compared with the GRiST expert judgements.

Table 7.9: Patient level comparisons:

Category	**Expert Risk Judgements**	**FG Results –** this refers to the % of the FG results that tally with the expert judgements per category	**FG Results Breakdown by Category –** this looks at the % of the FG in light of all categories (low, medium and high) and is thus directly comparable to the expert judgements
Low	71.7%	53% of Low	**38%(low);** 26.5%(medium); 6.6%(high)
Medium	22.0%	58% of Medium	4.5%(low); **12.8%(medium);** 4.7%(high)
High	6.3%	71.5% of High	0.52%(low); 1.3%(medium); **4.5%(high)**

This information can also be seen in the confusion matrix (Kohavi and Provost, 1998) depicted in table 7.10.

7.4.2 Discussion

From table 7.9 above, we see that 71.7% of the total patient cases (for values 1 to 10) were categorised as **low** risks by the experts. Of these 71.7%, 58% were also categorised as being low risk by the factor graph algorithm. This translates to 38% of the dataset (over categories low, medium and high). It is also both interesting and important to note in the FG categorisation the bulk of the remaining cases that were not categorised to low (but which were categorised to low by the expert judgements) were categorised to the closest category to low i.e. medium (26.5% of the whole dataset) and not to high (which had just 6.6% categorised to it of the cases that had been categorised to low by via expert judgements).

Examining the medium category in a similar manner to the low category. It can be seen that of the 22% of the entire cases that were categorised to medium via expert judgements, 58% of this 22% were also categorised to medium via the FG algorithm (this translates to an equivalent of 12.8% of the full dataset covering low, medium and high). Examining the spread of the remaining cases that were assigned to medium via expert judgements we see from the table above that 4.5% were assigned to low and 4.7% assigned to high which is almost an even spread in both directions, as the medium category sits in between these two categories and one is not necessary closer to it than the other this observation does not seem illogical.

Finally when we consider the high category, it can be seen that of the 6.3% of the entire dataset that were assigned to high via expert judgements 71.5% of these were also assigned to high via the factor graph. This is a significantly high percentage and again when compared to the entire dataset translates to 4.5% of the entire dataset over low, medium and high being categorised to high. From the table we see that 0.52% of these cases were assigned to low and 1.3% to medium, again like in the case of the low category, the larger proportion not assigned to the same category as the expert judgements was assigned to the category closest to the expert judgement (in the case the closest category being the medium category).

The above findings can be summarised as follows

- Expert judgements assigned 6.3% of the cases to high, of these 6.3%, the FG method categorised 4.5% to high too, 1.3% to medium and 0.52% to low.
- Expert judgements categorised 22% to medium, of these 22%, the factor graph technique assigned 12.8% to medium too, and the 4.5% to low and 4.7% to high.
- Finally via expert judgements 71.7% were categorised to low, of which 38% were also assigned to low via the FG algorithm. A further 26.5% of these were then assigned to medium and 6.6% to high.

Table 7.10: Confusion matrix depicting for the three categories; low, medium and high

	Low (%)	Medium (%)	High (%)	Classification Overall (%)	Producer Accuracy (Precision)
Low	**38.00**	4.50	0.52	43.02	88.33
Medium	26.50	**12.80**	1.30	40.60	31.53
High	6.60	4.70	**4.50**	15.80	28.48
Truth Overall	71.70	22.00	6.30	100	
User Accuracy	53.00	58.18	71.43		

In the confusion matrix depicted in table 7.10, the user accuracy and producer measures give us estimates of accuracy of the results. The user accuracy shows the accuracy of the results obtained from the GRiST probabilistic graphical model as a percentage of correctly categorised components divided by the total number of components in the category. The diagonal elements (highlighted in bold in table 7.10) represent the correctly categorised components. Finally, the overall accuracy of the categorisation can also be obtained from the confusion matrix in table 7.10 as follows:

Overall accuracy from confusion matrix = values correctly classified for each category / overall % classified

Overall accuracy = (38.00 + 12.80 + 4.50)/100 = 45.3

7.5 Conclusion

In this chapter the implementation of the GRiST probabilistic graphical model has been discussed, including the construction of the GRiST chain graph, parameter learning and conversion of the chain graph to factor graph. Analysis was also carried out on the model and the results from the factor graph inference compared to the expert judgements. The results showed an overall accuracy of 45.3 percent for the GRiST probabilistic graphical model in comparison to expert judgement. On the face of it this is not a good indication of a trend for correlation between the expert judgements and the graphical structure and the model as it stands cannot be used as a sole method for determining risk. However, when we considered the accuracy of the probabilistic model for the individual categories (i.e. low, medium and high), it can be seen that the model predicts well whether a patient is high risk (i.e. values 7 to 10) or not high risk (i.e. 1 to 6). This makes the model a good candidate for a mental health risk assessment decision support system, and can be used to highlight the patients that need additional assessment (using alternate methods such as expert judgements or the GRiST fuzzy model). The model therefore can be seen to have use as an alternative method for identifying high risk patients.

In the next chapter we conclude and discuss possible future directions for the GRiST probabilistic model, implementation of some of these ideas might improve the overall accuracy of the model.

Chapter Eight

8. Conclusions and Further Research

In this chapter we discuss the various methods and results from the processes used, the limitations of the processes, and problems encountered and possible future directions for the research.

8.1 Contributions

This research has focused on the process of developing a principled approach for translating a model of mental-health risk expertise into a probabilistic graphical structure. The nature of the research has involved exploring different areas. Areas ranging from the fuzzy logic domain, to psychological models, semantics of knowledge structures and ontologies and finally probabilistic graphical knowledge. This has made it a particularly interesting journey.

We started by dissecting the GRiST fuzzy knowledge structure in a bid to capture from the fuzzy / psychological model everything that could help in the accurate mapping to appropriate probabilistic graphical models. The main objective of the research was to develop a mental health risk assessment tool based on probabilistic graphical models. As noted in Chapter 2, the issue of bridging the gap between fuzzy logic and probability theory is a long drawn ongoing area of contention. However, we were able to circumvent this issue by basing our conversion rules on all the information that can be obtained from the GRiST fuzzy model. These include the GRiST uncertainty representations (based on membership grades and relative influences), the constraints inherent in the knowledge structure, the GRiST knowledge structure semantics, the relationship types between the variables in the knowledge structure and the visualisations of GRiST. From these we were then able to develop a set of mapping rules to guide the conversion of the expert based GRiST knowledge structure into probabilistic graphical structures.

The methods discussed in this thesis could be applicable to other systems based on hierarchical expertise, especially ones that contain both causal and non-causal relations. The entire research contributes to the area of risk assessments, and the conversion of knowledge-based systems using hierarchical expertise into probabilistic graphical models and contributes to the possibility of representing complex domains which encapsulate both causal and non causal relations in a way that more accurately represents such domains and as such has direct impact on the quality of the risk assessments obtained using the model.

8.2 Possible Future Directions

We believe that the methods discussed in this research may have applicability for other knowledge-based systems using hierarchical expertise, and in particular as a viable and effective alternative to trying to induce accurate probability graphs from a data set (which can be notoriously difficult). The approach outlined in this research shows that it can become more tractable by exploiting the structure induced from domain experts. In this section some offshoots from this research that could further extend the success of the research are highlighted as potential future directions for the research.

8.2.1 Expansion of Learning Algorithms

In this thesis the Expectation-Maximisation (EM) algorithm (Chapters 6 and 7) was used for learning the parameters. This proved to be a successful choice for the learning process, however it might still prove productive to expand the possible algorithms to determine if one that will give even better results exists or can be developed (e.g. developing a variant of the EM algorithm). Any discovering of an algorithm that gives an even better fit than the current EM algorithm will be a distinct advantage because the learned parameters directly influence the quality of the risk predictions obtained from the model.

8.2.2 Consideration of Additional Probability Building Blocks

In addition to the issue of the learning algorithm, the approach used in this research has been to map the GRiST component structures into probability building blocks, which are then combined to give a final chain graph. This approach has proved to be effective and made it possible to model both the causal and non causal parts of the GRiST knowledge structure correctly. However, we believe that in future work this can be improved on. This improvement can be brought about by broadening the possible probability building blocks that the GRiST component structures can map to. The rationale behind this being that the more accurately the final model represents the domain, the more accurate will the predictions from it be. This will possibly involve breaking the knowledge structure into more fine grained components and seeing if there are additional probability structures that these fine grained components naturally map to. To illustrate this, for example in the current research an assumption was made that within a component structure all the nodes are related by the same type (i.e. they are either all causal or non causal). However there will be instances where a component structure can be more accurately modelled if it is mapped to a probability building block that does not force a decision to be made on whether its causal or non causal if it happens to be a mixture of these.

An example of such a potential building block is the tree structured conditional random field (TS-CRF). A conditional random field (CRF) is similar to an MRF in that it is an undirected graph but unlike the MRF, it encodes a conditional distribution *P(Y|X)* (Koller and Friedman, 2009), where *X* is a set of observed nodes and *Y* are unobserved nodes (this can correlate directly with the notion of datum and concept nodes respectively in the GRiST knowledge structure). Consider a fixed generic component structure such as g*en-depression* (Figure 5.4) which is a high level structure and is fairly complex as it is made up of several other fixed generic component and generic distinct component structures. To model it as a TS-CRF, the important dependencies to identify, are all parent to child, siblings and internal nodes to root dependencies (i.e. for every internal node to root node, there must be a path that links the two together).

Examples of parent to child relationships in this structure are *gen-hopeless* to *gen-plans-future* and so on. Sample sibling relationships are *gen-dep-stage* and *serious-depression*. An example of internal node to root node dependency can be seen between *gen-jealous* and *gen-depression*, in this case the path that links these two goes from *gen-jealous* to *gen-feel-emot* to *serious-depression* and finally to *gen-depression*. A TS-CRF allows us to model hierarchy relations of the form $P(Y \mid X)$ where *Y* is unknown and *X* is known. In our case *X* represents the set of datum nodes that are directly connected with the fixed generic component structure, whilst *Y* represents the fixed generic component structures concept nodes. The equation that defines this is depicted below and has been taken from (Tang et al, 2006).

Let (y_p, y_c) be the dependency between a parent and a child vertices , (y_c, y_p) the dependency between child and parent and (y_s, y_s) between siblings. Then,

$$P(y|x) = \frac{1}{Z(x)} \exp\left(\sum_{e \in \{E^{pc}, E^{cp} E^{ss}\}, j} \delta_j \, t_j(e, y|_e, x) + \sum_{v \in V, k} \mu_k S_k(v, y|_v, x) \right).$$

Where E^{PC} represents the set of (y_p, y_c) etc and t_j and s_k are feature functions.

Thus the TS-CRF allows us to model the independency assertion encoded in the high level fixed generic component structure, and might prove to be better than the current representation. The TS-CRF was not used in the current research because it was not proven to be the case that within a component structure based on the current version of the GRiST knowledge structure that there will be mixed relationship types (i.e. both causal and non causal). However, if the GRiST knowledge structure is re-visited and found to contain these additional constraints then an extension such as this will be worth considering.

8.2.3 Structure Learning

The structure of the current probabilistic graphical model has been based entirely on human expertise (encapsulated in the GRiST fuzzy model). In contrast, and in spite of the complexity involved in learning structure from data, it will be interesting and potentially informative to learn the structure from data directly. However, this is not suggested as a potential extension to the current research but more as a useful complement that can potentially be used as another basis for comparison of results. It might also potentially be used to feedback to the fuzzy model and provide improvements to it (which could in turn influence the probabilistic model).

8.3 Limitations and Problems Encountered

In the learning of the parameters from the GRiST data, it was clearly seen that the more data was used for the training the more accurate the produced results. This in turn means that the results achieved were limited to the amount of data available, 9417 cases which had to be split into training and test data for the learning process (different approaches were explored to increase the test data). Another limitation was in the available tool for the construction of the chain graph. The Bnet and Pmtk3 toolkits for MATLAB provided a good set of algorithms and functions, it could not handle the loading and processing of the entire graph structure in a single go. The embedded approach discussed in Chapter 6, provided a solution to this. However, some of the commercial tools (e.g. Hugin) are supposed to be able to handle thousands of nodes in a graph; such a tool might have been useful.

Overall the methods used in this thesis have been successful and can potentially be further improved by the implementation of some of the extensions suggested in this chapter.

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Appendix 1

Full Listings of GRiST knowledge Structure Node Code Names and their Descriptive Labels.

Node Name	Descriptive Label		Node Name	Descriptive Label
Suic	Suicide		gen-accm-share-nd	number of non-dependents sharing accommodation
suic-past-att	past and current suicide attempts		gen-accom-depndnts	Dependents
suic-curr-int	current intention to commit suicide		gen-accom-state	state of accommodation
suic-int-p-trig	potential triggers for prospective suicide		gen-body-face	body language and expression
suic-ideation	suicidal ideation		gen-cog-think-mem	thinking processes and memory
suic-bhvr-const	constraints on suicidal behaviour		gen-concentr	concentration
suic-app-behvr	person's appearance and behaviour at assessment indicating suicide		gen-congruence	congruence of physical, verbal, and emotional presentation
suic-s-h-behv	self-harm behaviour indicative of suicide		gen-day-actvty-lev	general level of activity during the day
suic-fam-hist	family history of suicide		gen-day-struct	structure of day
gen-feel-emot	feelings/emotions		gen-dep-stage	stage of depression
gen-self-worth-p	person's perspective of self worth		gen-diet-drink	drinking
mental-health	mental health problems		gen-diet-eating	eating
ment-fac	mental faculties/cognitive capacity		gen-diet-weight	weight

Node Name	Descriptive Label		Node Name	Descriptive Label
gen-personality	Personality		gen-engagement	person's engagement with assessor
motive-eng	motivation and engagement with world		gen-forensic-proc	forensic/criminal proceedings
gen-soc-contxt	social context		gen-home-type	type of home
gen-currnt-bhvr	general current behaviour		gen-insght-behvr	insight into behaviour and consequences
gen-subs-misuse	substance misuse		gen-job-chg-frq	frequency of changing jobs
insight-resp	insight and responsibility		gen-life-abuse	abuse to person
gen-phys-hlth-prb	physical health problems		gen-life-not-livng	life not worth living
gen-meds-therpy	concordance with health services/medication/therapie s		gen-mental-withd	mental withdrawal
adv-life-event	adverse life events		gen-mentl-insght	insight into mental-health problems
gen-demog	Demographics		gen-mntl-cur-sympt	current symptoms of severe mental illness
gen-accom-share	occupants sharing accommodation		gen-move-freq	frequency of moving accommodation
gen-age	Age		gen-nd-hlp-diff	need for help with difficulties
gen-alc-misuse	detrimental effects of alcohol misuse		gen-neighbrhd	neighbourhood
gen-angry-emotns	angry emotions		gen-net-relat	external network of relationships
gen-anx-emotns	anxiety-based emotions		gen-perc-debt-anx	anxiety about perceived level of debts
gen-app-diet	appropriateness of diet		gen-phys-withd	physical withdrawal from world

Node Name	Descriptive Label		Node Name	Descriptive Label
gen-assertive	Assertiveness		gen-plans-future	plans for the future
gen-chall-bhvr	challenging behaviour		gen-poverty	chronic poverty
gen-com-imp	communication impairment		gen-rec-bad-job-ch	recent or potential detrimental change to employment
gen-controlling	controlling/organisational approach		gen-recent-life-trauma	recent traumatic life changes
gen-coping-abil	capacity to cope with major life stresses		gen-relat-detr-chg	detrimental changes to relationships
gen-day-actvty	daily activity		gen-relat-nature	nature of relationships
gen-dependence	Dependence		gen-resp-impct-oth	responsibility for impact of behaviour on others
gen-depression	Depression		gen-risk-verbal	verbal indicators of risk
gen-distress	Distress		gen-sh-cuts	self-harming cuts
gen-drug-misuse	detrimental effects of drugs misuse		partner-share-acc	partner sharing
gen-eating-dis	eating disorders		serious-depression	Seriousness of current depression
gen-educ-expr	educational experience		sn-appearnce	appearance indicators of self neglect
gen-empathy-abil	ability to empathise		suic-leth-insght	insight into lethality of previous suicide attempts
gen-employment	Employment		suic-most-rec	most recent suicide attempt
gen-eng-world	engagement with world		suic-note-prev	suicide note written for one or more previous attempts
gen-env-grew-up	environment person grew up in		suic-patt-att	pattern of suicide attempts

Node Name	Descriptive Label		Node Name	Descriptive Label
gen-ethnicity	Ethnicity		suic-plan-dtail	level of detail and clarity of suicide plan
gen-finance-prob	financial problems		suic-planning	How much planning was generally involved in the suicide attempts
gen-gender	Gender		suic-plan-real	realism of suicide plan
gen-helpless	Helplessness		suic-prosp-leth	potential lethality of prospective suicide method
gen-hopeless	Hopelessness		suic-ser-method	seriousness of suicide methods
gen-hostile	Hostility		suic-steps-takn	physical steps taken to implement suicide plan
gen-impaird-cog	impaired cognitive function		suic-thght-prev	thoughts/feelings related to previous suicide attempts
gen-insght-behvr	insight into behaviour and consequences		suic-first-occ	first time suicide attempt occurred
gen-jealous	Jealousy		suic-how-many	how many suicide attempts
gen-learn-disab	learning disabilities		suic-escalate	suicide attempts escalating in frequency
gen-life-trauma	traumatic experiences		suic-discovery	chance of discovery after suicide attempts
gen-listless	listless, no energy, slowed down, loss of drives		suic-lethality	potential lethality of suicide method
gen-living-arr	living arrangements		suic-ser-succd	How much did the person want to succeed with the suicide attempts

Node Name	Descriptive Label		Node Name	Descriptive Label
gen-marital-status	marital status		suic-regret	regret about trying to commit suicide
gen-med-perc-benft	perceived benefit of medication/therapies		sn-hair-clothes	hair and clothing indicative of self neglect
gen-meds-concord	Concordance		sn-hygiene	personal hygiene
gen-mood-swings	mood swings/lability		sn-recnt-app-chnge	recent change in appearance of self neglect
gen-motivation	general motivation in life		sn-skin	skin
gen-nd-hlp-diff	need for help with difficulties		gen-rapport	rapport/empathy
gen-negative-self	negative feelings about the self		gen-responsve	person's responsiveness
gen-phys-hlth-deg-diag	when life-threatening or degenerative illness first diagnosed		gen-gut-assmnt	assessor's uneasiness about the person
gen-phys-hlth-det	deterioration in physical health		gen-risk-tone	tone
gen-phys-hlth-disa	Disability		gen-coherence	degree to which the person is making sense
gen-phys-hlth-pain	Pain		gen-distrss-b-lang	body language indicating distress
gen-presentation	person's behavioural presentation during assessment		gen-low-mood	movements, posture, facial expression indicating low mood
gen-relatnshps	Relationships		gen-threat-move	aggressive/threatening movements, posture, or expression
gen-reliable	Reliability		gen-detached	preoccupied/detached demeanour
gen-resp-impct-oth	responsibility for impact of behaviour on others		gen-eyes	eyes

Node Name	Descriptive Label		Node Name	Descriptive Label
gen-rsk-behavr	reckless risk taking		gen-feel-emot	feelings/emotions
gen-sad	sad/downbeat		gen-self-worth-p	person's perspective of self worth
gen-ser-mentl-ill	serious mental illness		gen-motivation	general motivation in life
gen-serv-last-acc	time since person accessed services		gen-voice-hal	voice hallucinations
gen-serv-perc-supp	person's perception of the supportiveness of service received		gen-paranoid-del	paranoid delusions
gen-sleep-dist	sleep disturbance		gen-impaird-cog	impaired cognitive function
gen-unint-risk-behavr	unintentional risk making		gen-currnt-bhvr	general current behaviour
gen-unusl-rec-bhvr	uncharacteristic recent change in behaviour		gen-presentation	person's behavioural presentation during assessment
grandiosity	Grandiosity		gen-eng-world	engagement with world
insight-resp	insight and responsibility		gen-mania	mania/hypomani a
suic-eol-prep	end-of-life preparations for intended suicide act		gen-voice-hal	voice hallucinations
suic-id-control	ability to control suicidal ideation		gen-paranoid-del	paranoid delusions
suic-id-freq	frequency of suicidal ideation		gen-relat-supp	supportive relationships
suic-id-hi-risk	content of suicidal ideation indicates high risk		gen-relat-detr	detrimental relationships
suic-id-strngth	strength, intensity, intrusiveness, and persistence of suicidal ideation		gen-isol-accom	isolated accommodation
suic-int-inform	informed someone about intention to commit suicide		gen-neigbrhd-rsky	risky neighbourhood
suic-occur	occurrence of suicide attempt		gen-accom-hm-care	care of home

Node Name	Descriptive Label		Node Name	Descriptive Label
suic-person-per	person's current perspective on suicide attempts		gen-accom-habitbl	habitable accommodation
suic-phys-indic	physical indicators of suicide		gen-diet-weigt-ext	person's weight
suic-plans	plans and methods for committing suicide		gen-diet-weigt-chg	extreme weight change
suic-pot-trig	potential triggers of suicide		gen-relat-detr-chg	detrimental changes to relationships
suic-prep-serious-at	preparation and seriousness of suicide attempts		gen-perc-debt-anx	anxiety about perceived level of debts
suic-p-trig-mtch	potential triggers match those that previously caused suicide attempts		gen-rec-bad-job-ch	recent or potential detrimental change to employment
suic-rel-belief	religious values/beliefs affecting suicide risk		gen-phys-hlth-deg-diag	when life-threatening or degenerative illness first diagnosed
worthlessness	Worthlessness		gen-life-sex-abuse	sexual abuse
			gen-phys-abse	physical abuse
			gen-emot-abse	emotional abuse
			gen-financial-abuse	financial abuse
			gen-accom-num-dep	number of dependents
			gen-dep-ygnst-age	age of youngest dependent
gen-risk-aggrsv	degree of aggression/hostility		gen-plans-future	plans for the future
gen-risk-upbeat	how upbeat or downbeat/depressed		gen-life-not-livng	life not worth living
gen-avoid-eye-contact	avoid eye contact		gen-voice-dang-s	danger of voices to self
gen-eye-movement	eye movement		gen-voice-dang-o	danger of voices to others

Node Name	Descriptive Label		Node Name	Descriptive Label
gen-mood-swngs	mood swings/lability		gen-paran-del-spec	about specific individuals
gen-negative-self	negative feelings about the self		gen-paran-del-pers	being harmed, killed, or persecuted
gen-angry-emotns	angry emotions		gen-diet-eating	eating
gen-anx-emotns	anxiety-based emotions		gen-diet-weight	weight
gen-helpless	helplessness		gen-diet-drink	drinking
gen-sad	sad/downbeat		gen-day-struct	structure of day
gen-distress	distress		gen-day-actvty-lev	general level of activity during the day
gen-jealous	jealousy		gen-rapport	rapport/empathy
gen-hopeless	hopelessness		gen-responsve	person's responsiveness
grandiosity	grandiosity		gen-gut-assmnt	assessor's uneasiness about the person
worthlessness	worthlessness		gen-risk-tone	tone
gen-voices-type	type of voices		gen-coherence	degree to which the person is making sense
gen-prob-act-voice	likelihood of acting on the voices		gen-distrss-b-lang	body language indicating distress
gen-type-paranoid-del	type of paranoid delusions		gen-low-mood	movements, posture, facial expression indicating low mood
gen-prob-act-par-del	likelihood of acting on delusions		gen-threat-move	aggressive/threatening movements, posture, or expression
gen-cog-think-mem	thinking processes and memory		gen-detached	preoccupied/detached demeanour
gen-concentr	concentration		gen-eyes	eyes
gen-rsk-behavr	reckless risk taking		gen-voice-dang-s	danger of voices to self

Node Name	Descriptive Label		Node Name	Descriptive Label
gen-unint-risk-behavr	unintentional risk making		gen-voice-dang-o	danger of voices to others
gen-sleep-dist	sleep disturbance		gen-paran-del-spec	about specific individuals
gen-app-diet	appropriateness of diet		gen-paran-del-pers	being harmed, killed, or persecuted
gen-unusl-rec-bhvr	uncharacteristic recent change in behaviour		gen-diet-weigt-ext	person's weight
gen-chall-bhvr	challenging behaviour		gen-diet-weigt-chg	extreme weight change
gen-day-actvty	daily activity		gen-risk-aggrsv	degree of aggression/hostility
gen-engagement	person's engagement with assessor		gen-risk-upbeat	how upbeat or downbeat/depressed
gen-risk-verbal	verbal indicators of risk		gen-avoid-eye-contact	avoid eye contact
gen-body-face	body language and expression		gen-eye-movement	eye movement
gen-congruence	congruence of physical, verbal, and emotional presentation		gen-prob-act-par-del	likelihood of acting on delusions
gen-phys-withd	physical withdrawal from world		gen-sex-abse-last	most recent episode of sexual abuse
gen-mental-withd	mental withdrawal		gen-sex-abse-as-ch	sexual abuse during childhood (0 to 16)
gen-voices-type	type of voices		gen-phys-abse-last	most recent episode of physical abuse
gen-prob-act-voice	likelihood of acting on the voices		gen-phy-abse-as-ch	physical abuse during childhood (0 to 16)
gen-type-paranoid-del	type of paranoid delusions		gen-emot-abse-last	most recent episode of emotional abuse

Appendix 2

GRiST Full Questionaire for Working Age Adults (Ages 18 – 65)

Person's name: .... *Date of birth:* ☐ d ☐ m ☐ y

Gender: ☐ *male* ☐ *female*

Marital status: ☐ *single (never married)* ☐ *married (first marriage)* ☐ *remarried*
☐ *separated but legally married* ☐ *divorced* ☐ *widowed*

Does the person share his or her living accommodation with anyone (if no, ignore all indented questions, as explained in the instructions)? .... *yes* ☐ *no* ☐

Does the person live with any dependents (older relatives or children)? .... ☐ *yes* ☐ *no*

☐ *number of dependents* ☐ *Approximate age of youngest dependent*

Which non-dependents share the Living accommodation (tick all that apply)?. ☐ *partner* ☐ *carer* ☐ *friends/communal* ☐ *other service users* ☐ *sibling(s)* ☐ *parent(s)* ☐ *other relatives*

Please tick the most appropriate ethnic group for the person

White: ☐ British ☐ Irish ☐ other white background

Mixed: ☐ white/black Caribbean ☐ white/black African ☐ white/black Asian ☐ other mixed background

Asian: ☐ Indian ☐ Pakistani ☐ Bangladeshi ☐ other Asian background

Black: ☐ Caribbean ☐ African ☐ other black background

☐ Chinese ☐ other ethnic background

RISK SUMMARY

	0	1	2	3	4	5	6	7	8	9	10	dk
Suicide.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Self harm	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Self neglect.												☐
Harm to others /damage to Property. .	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Vulnerability	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Risk to dependents	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

OVERALL RISK COMMENTS

ACTION PLAN

(See page 16 for instructions on how to complete the form)

Rapid screening questions

SCREENING QUESTIONS LINKED TO A PARTICULAR RISK

SUICIDE

Has the person ever made a suicide attempt? *If yes, → p6* .... ☐ *yes* ☐ *no* dk ☐

Are you concerned about the person's current intention to commit suicide? *If yes, →p6* .... ☐ *yes* ☐ *no* dk ☐

Are you concerned about the person being exposed to circumstances or emotions that could trigger suicide attempts? *If yes, → p7* .... ☐ *yes* ☐ *no* dk ☐

Is the person having suicidal thoughts or fantasies? *If yes, → p7* .... ☐ *yes* ☐ *no* dk ☐

SELF-HARM

Has the person ever engaged in self-harming behaviour? *If yes, → p7* .... ☐ *yes* ☐ *no* dk ☐

Are you concerned about the person being exposed to circumstances or emotions that could trigger self-harm? *If yes, → p7* .... ☐ *yes* ☐ *no* dk ☐

Is the person having self-harming thoughts or fantasies? *If yes, → p8* .... ☐ *yes* ☐ *no* dk ☐

HARM TO OTHERS OR DAMAGE TO PROPERTY

Has the person ever engaged in episodes of harm to people/animals or damage to property (fire setting, vandalism, etc)? *If yes, → p8 but also record the most important information below* .... ☐ *yes* ☐ *no* dk ☐

Tick all groups of people who are Known to have been the target of any harm by the person. .... ☐ *people in domestic setting* ☐ *health and social care workers* ☐ *friends/acquaintances/work colleagues* ☐ *ethnic groups* ☐ *authority figures*

Were any of the episodes physical or sexual assaults/abuse? *If yes, → p8* .... ☐ *yes* ☐ *no* dk ☐

– Has the person ever engaged in fire setting behaviour? *If yes, → p8* .... ☐ *yes* ☐ *no* dk ☐

Do you believe the person has an intention to cause harm or damage? *If yes, → p9* .... ☐ *yes* ☐ *no* dk ☐

Are you concerned about the person being exposed to circumstances or emotions that could trigger harm or damage? *If yes, → p9* .... ☐ *yes* ☐ *no* dk ☐

Is the person having thoughts or fantasies about harming people/animals or damaging property? *If yes, → p9* .... ☐ *yes* ☐ *no* dk ☐

Are there any child protection issues? .... ☐ *yes* ☐ *no* dk ☐

SELF NEGLECT

Are you concerned about the person being at risk of self neglect or neglect by others? *If yes, → p10* .... ☐ *yes* ☐ *no* dk ☐

VULNERABILITY OF SERVICE USER

Does the person have a history of falls or other accidents? *If yes, → p10* .... ☐ *yes* ☐ *no* dk ☐

Are you concerned about any other issues that may be putting the person at risk due to his or her vulnerability (consider physical, emotional, sexual, and financial vulnerability)? *If yes, → p10* .... ☐ *yes* ☐ *no* dk ☐

RISK TO DEPENDENTS?

Are you concerned about risks to dependents? *If yes, → p5* .... ☐ *yes* ☐ *no* dk ☐

SCREENING QUESTIONS RELEVANT TO MORE THAN ONE RISK

Are you concerned about risks due to the person's **feelings/emotions**? *If yes, → p11* ..	☐ *yes*	☐ *no*	dk ☐
Are you concerned about risks due to the person's sense of **self worth**? *If yes, → p11*	☐ *yes*	☐ *no*	dk ☐
Is there any history of **depression or serious mental illness**, including any current episode? *If yes, → p11*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about risks due to the person's **mental faculties/cognitive capacity**? *If yes, → p12*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about **personality factors** and their impact on risks? *If yes, → p12*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about the person's **motivation and engagement with the world**? *If yes, → p12*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about risks due to the person's **social context** (relationships, living arrangements, finances, employment, any detrimental changes)? *If yes, → p13*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about the person's **general current behaviour** (eg risk-taking, sleep patterns, daily activities, challenging behaviour)? *If yes, → p13*	☐ *yes*	☐ *no*	dk ☐
Does the person have a history of misusing **drugs or alcohol**? *If yes, → p14*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about the person's lack of **insight and sense of responsibility**? *If yes, → p14*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about risks due to any **physical health problems**? *If yes, → p14*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about the person's **concordance** with mental-health treatment? *If yes, → p14*	☐ *yes*	☐ *no*	dk ☐
Does the person have a history of **adverse life events** (eg suffered abuse, criminal justice proceedings, detrimental upbringing/education, eating disorders)? *If yes, → p15* *Consider also social context (p.13) and physical health (p.14).*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about the person's **behavioural presentation** with respect to potential risks (eg verbal and physical behaviour, uneasy 'gut' feeling in yourself)? *If yes, →p15*	☐ *yes*	☐ *no*	dk ☐
Are you concerned about the person's **diet**? *If yes, → p16*	☐ *yes*	☐ *no*	dk ☐

END OF SCREENING QUESTIONS

General comments

Risk judgements

Please use your judgement to assess the risks associated with the person, incorporating information you have obtained from the screening questions and the additional information associated with them. When you have finished, don't forget to copy the risk judgement scores to the front-page summary.

SUICIDE: In your judgement, to what extent is the person at risk of suicide?

min			low		medium		high			max	dk
0	1	2	3	4	5	6	7	8	9	10	dk
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Comments

SELF-HARM: In your judgement, to what extent is the person at risk of self-harm?

min			low		medium		high			max	dk
0	1	2	3	4	5	6	7	8	9	10	dk
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Comments

SELF NEGLECT: In your judgement, to what extent is the person at risk of self- neglect?

min			low		medium		high			max	dk
0	1	2	3	4	5	6	7	8	9	10	dk
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Comments

HARM TO OTHERS OR DAMAGE TO PROPERTY: In your judgement, to what extent is the person at risk of causing harm to people/animals or damaging property?

min		low		medium		high		max			dk
0	1	2	3	4	5	6	7	8	9	10	
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Comments

VULNERABILITY OF SERVICE USER: In your judgement, to what extent is the person at risk due to his or her vulnerability (consider physical, emotional, sexual, and financial vulnerability)?

min		low		medium		high		max			dk
0	1	2	3	4	5	6	7	8	9	10	
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Comments

RISK TO DEPENDENTS: In your judgement, to what extent does the person put dependents at risk, if any (consider both chil- dren and adults but answer zero if there are no dependents)?

min		low		medium		high		max			dk
0	1	2	3	4	5	6	7	8	9	10	
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Comments

Additional questions specific to a particular risk

These questions only need to be answered if flagged by the screening questions as relevant or appropriate for this particu- lar assessment. Indented questions can also be ignored if the root (filter) question is 'no' or 'dk' (don't know).

Additional questions for SUICIDE

Further questions on past and current suicide attempts

– When was the last suicide attempt? .... ☐ d ☐ m ☐ y dk ☐

– Has there been more than one suicide attempt? .... ☐ yes ☐ no dk ☐

– When was the first suicide attempt? .... ☐ d ☐ m ☐ y dk ☐

– Approximately how many suicide attempts have there been? .... ☐ approx dk ☐

– How have the suicide attempts been changing in frequency over the last two years? .... ☐ decreasing ☐ same ☐ increasing dk ☐

– To what extent were the suicide attempts well planned? .... min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– Was a suicide note written for any previous or current suicide attempts? . . . ☐ yes ☐ no dk ☐

– To what extent were the suicide attempts concealed to prevent discovery? min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

How lethal was the most serious method used by the person in any of the Suicide attempts (i.e. how likely to succeed in killing the person without any intervention)? 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent do you believe the person wanted the suicide attempts to succeed at the time? .... 0 1 2 3 4 5 6 7 8 9 10 dk

How much does the person fail to show any regret or remorse over having tried to commit suicide in the past? .... 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person lack awareness about how dangerous the suicide attempts were? .... 0 1 2 3 4 5 6 7 8 9 10 dk

Further questions on current intention to commit suicide

– Does the person have any plans for making a future suicide attempt? . . . . . . ☐ yes ☐ no dk ☐

To what extent can the person easily carry out the suicide plan (consider realism of plan, access to means of putting it into effect, and any collusion with others)? min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– How clear and detailed is the suicide plan? .... 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent has the person taken steps towards implementing the suicide plan? .... 0 1 2 3 4 5 6 7 8 9 10 dk

– How likely is the chosen method to succeed once the attempt has started?. . . . 0 1 2 3 4 5 6 7 8 9 10 dk

– Has the person told anyone about an intention to commit suicide? .... ☐ yes ☐ no dk ☐

To what extent has the person made end-of-life preparations matching those that would cause you most concern about suicide risk (eg written a will, sorted finances, put house in order, written suicide note)? .... min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

Further questions on potential triggers for prospective suicide

To what extent is the person exposed to circumstances or emotions that may trigger a suicide attempt? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent do the person's current emotions or circumstances match those that are known to have triggered previous suicide attempts? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

Further questions on suicidal ideation

– To what extent does the person lack ability to control suicidal thoughts or fantasies? 0 1 2 3 4 5 6 7 8 9 10 dk

– How much does the content of the suicidal thoughts or fantasies raise serious con- cerns about suicide risk? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

– How often do the suicidal thoughts or fantasies occur? ☐ *daily* ☐ *weekly* ☐ *monthly* ☐ *less* dk ☐

– How persistent, intrusive, or intense are the suicidal thoughts? . . . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

General suicide questions

What effect do the person's religious values, beliefs, or attitudes to dying have on risk of suicide? . . . . ☐ *strongly reduce* ☐ *reduce* ☐ *no effect* ☐ *increase* ☐ *strongly increase* ☐ *dk*

To what extent does the person have a pattern of self-harming that indicates suicide risk? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

Has there been any history of suicide attempts in the person's family? . . . . . ☐ *yes* ☐ *no* dk ☐

Additional questions for SELF-HARM

Further questions on past and current episodes of self-harm

– When was the last self-harm episode? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

– Has there been more than one self-harm episode? . . . . ☐ *yes* ☐ *no* dk ☐

– When was the first self-harm episode? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

– Approximately how many episodes of self-harm have there been? . . . . . ☐ *approx* dk ☐

– Are the self-harm episodes increasing or decreasing in frequency over the last two years? . . . . ☐ *decreasing* ☐ *same* ☐ *increasing* dk ☐

– How much planning was generally involved in the self-harm episodes? min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent are the self-harming attempts concealed to prevent discovery? . . 0 1 2 3 4 5 6 7 8 9 10 dk

– In general, how likely is it that the chosen self-harm methods could lead to death? 0 1 2 3 4 5 6 7 8 9 10 dk

– How much were the self-harm episodes more than a cry for help? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

– Did the self-harm episodes help the person cope with difficulties? . . . . ☐ *yes* ☐ *somewhat* ☐ *no* dk ☐

Further questions on potential triggers for prospective self-harm

To what extent is the person exposed to circumstances or emotions that may trigger self-harm episodes? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent do the person's current emotions or circumstances match those that are known to have triggered any previous episodes of self harm? 0 1 2 3 4 5 6 7 8 9 10 dk

Further questions on self-harm ideation

– How persistent, intrusive, and intense are the self-harming thoughts? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– How often do the self-harming thoughts or fantasies occur? ☐ *daily* ☐ *weekly* ☐ *monthly* ☐ *less* dk ☐

General self-harm questions

To what extent does the person display evidence of self-harming cuts? min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

Has there been any history of self-harm in the person's family? . . . . ☐ *yes* ☐ *no* dk ☐

Additional questions for HARM TO OTHERS OR DAMAGE TO PROPERTY

Further questions on past and current episodes of harm or damage

Further questions on any violent assault/physical abuse

– How serious was the most severe assault or physical abuse? . . .. min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– When was the first episode of assault/physical abuse? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

– When was the most recent episode of assault/physical abuse? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

Questions on sexual assault/abuse

– Were any of the assaults rape or some other form of sexual abuse? . . . . . ☐ *yes* ☐ *no* dk ☐

– Tick the most serious form of sexual assault by the person? . . . . ☐ *indecent exposure* ☐ *forcible fondling* ☐ *sexual assault with an object* ☐ *forcible oral or anal intercourse* ☐ *forcible rape* dk ☐

– When was the first episode of sexual assault? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

– When was the most recent episode of sexual assault? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

– Did any previous episodes of harm to others involve weapons (eg guns, knives)? ☐ *yes* ☐ *no* dk ☐

Further questions on any fire-setting

– How serious were the acts of fire setting? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– When was the first episode of fire setting? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

– When was the most recent episode of fire setting? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

Questions on emotional episodes of harm to others

– Has the person ever inflicted emotional cruelty on others (including racial abuse)? . . ☐ *yes* ☐ *no* dk ☐

– How serious was the emotional cruelty? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– When was the first episode of emotional cruelty? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

– When was the most recent episode of emotional cruelty? . . . . ☐ *d* ☐ *m* ☐ *y* dk ☐

Questions on destructive acts against property

– Has the person ever engaged in destructive acts concerning property (excluding fire setting)? . . . . ☐ *yes* ☐ *no* dk ☐

– How serious were the destructive acts concerning property? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– When was the first destructive act concerning property? . . . . d m y dk

– When was the most recent destructive act concerning property? . . . . . . d m y dk

Questions on abuse of animals

– Has the person ever abused animals? . . . . yes no dk

– How serious was the animal abuse? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– When was the first episode of animal abuse? . . . . d m y dk

– When was the most recent episode of animal abuse? . . . . d m y dk

General questions relating to any previous episodes of harm or damage

– Approximately how many episodes of all types of harm or damage are there known to have occurred? . . . . approx dk

– How are the episodes of harm or damage changing in frequency? decreasing same increasing dk

To what extent does the person continue to believe there was nothing wrong with causing harm or damage? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

Further questions on intention for harm or damage

To what extent does the person's plan for harm or damage match one that would cause you most concern? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person have the means and know-how for carrying out the plan to harm or damage? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent has the person taken steps towards implementing the plan to harm or damage (eg made threats, monitored the victim)? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

Has the person got any particular victims (specific individuals) in mind for harming?.................. yes no dk

Further questions on potential triggers for prospective harm or damage

To what extent is the person exposed to emotions or circumstances that could trigger episodes of harm or damage? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent do the person's current emotions or circumstances match those that have previously triggered episodes of harm or damage? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

Further questions on ideation about violence

To what extent does the content of the person's thoughts or fantasies raise serious concerns about risk of harm or damage? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

– How often do the thoughts or fantasies about harm or damage occur? daily weekly monthly less dk

– How persistent, intrusive, or intense are the thoughts/fantasies of harm or damage? . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent do the thoughts/fantasies of harm or damage relate to the people, events, and circumstances in the person's own world (ie the realism of the thoughts)? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

General questions on harm or damage

What effect do the person's religious values or beliefs have on the risk of harm or damage? .... ☐ *strongly reduce* ☐ *reduce* ☐ *no effect* ☐ *increase* ☐ *strongly increase* ☐ *dk*

To what extent is there a history of violence, abuse, or aggression in the person's family? .... min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person have an interest in pursuits related to violence (eg weapons, violent videos or computer games)? .... 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person's appearance (not body language or behaviour) match one that would cause you most concern about risk of harm or damage (eg sweating, blood, state of clothes)? .... 0 1 2 3 4 5 6 7 8 9 10 dk

Additional questions for SELF NEGLECT

To what extent do the person's hair and clothing indicate a failure to look after one- self? .... min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person have poor personal hygiene (eg smell, dirty hair and nails)? .... 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent has there been a recent change in appearance suggestive of failing to look after oneself? .... 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person's skin (condition, lesions, injuries, etc) indicate a failure to look after oneself? .... 0 1 2 3 4 5 6 7 8 9 10 dk

Additional questions for VULNERABILITY OF SERVICE USER

Further questions on falls

Have any of the falls or accidents occurred recently (within 6 to 9 months approximately)? .... ☐ *yes* ☐ *no* dk ☐

– Are the reasons for the falls or accidents known (eg physical health problems, hazards in the home)? .... ☐ *yes* ☐ *no* dk ☐

Further questions on person's appearance and behaviour indicators of vulnerability

To what extent does the person's appearance match one that would cause you most concern about vulnerability to abuse by others (eg bruises, scratches, blood, state of clothes)? .... min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent does the person's behaviour make the person vulnerable to sexual harrassment or abuse? .... 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent does the person's behaviour make the person vulnerable to physical harrassment or abuse? .... 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent does the person's behaviour make the person vulnerable to emotional harrassment or abuse? .... 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent does the person's behaviour make the person vulnerable to financial abuse? .... 0 1 2 3 4 5 6 7 8 9 10 dk

– Does the person have a history of wandering behaviour? .... ☐ *yes* ☐ *no* dk ☐

To what extent is the person dependent on carers? .... min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent is the person confused or disorientated as a result of recent changes in circumstances (eg hospital admission, new carer)? ... 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person lack the ability to look after daily living requirements (cooking, shopping, cleaning, etc)? .... 0 1 2 3 4 5 6 7 8 9 10 dk

Additional questions for information that is relevant to more than one risk

Further questions on feelings/emotions

	min low medium high max (0–10)	dk
– To what extent does the person have unstable moods or mood swings?	0 1 2 3 4 5 6 7 8 9 10	dk
To what extent does the person have negative feelings about him or herself (eg self-hatred, guilt, shame, humiliation)?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent is the person displaying anger?.	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person show anxiety (eg afraid, fearful)?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person feel helpless?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person seem sad or downbeat?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent is the person displaying or expressing distress?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent is the person expressing jealousy?	0 1 2 3 4 5 6 7 8 9 10	dk

Questions on hopelessness

– To what extent does the person lack any plans for the future?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person think life is not worth living?	0 1 2 3 4 5 6 7 8 9 10	dk

Further questions on person's perspective of self worth

	min low medium high max (0–10)	dk
– To what extent does the person have an exaggerated self-worth or grandiosity?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person regard him or herself as worthless?	0 1 2 3 4 5 6 7 8 9 10	dk

Further questions on mental health problems

– Does the person have any history of depression (past or present)?	☐ *yes* ☐ *no*	dk
– Tick the most appropriate label for the current episode of depression?	☐ *first episode* ☐ *relapse* ☐ *recovery (first)* ☐ *recovery (repeat)*	dk
– Does the person have any history of serious mental illness (past or present)?	☐ *yes* ☐ *no*	dk
– How much does the person lack insight into his or her mental-health problems? .	min low medium high max: 0 1 2 3 4 5 6 7 8 9 10	dk
– Is the person currently suffering from symptoms of a mental illness?	☐ *yes* ☐ *no*	dk
– To what extent is the person displaying manic or hypomanic behaviour (mood swings, fast speech, excessive irritability, recklessness, impulsivity, etc)?	min low medium high max: 0 1 2 3 4 5 6 7 8 9 10	dk

Questions on voice hallucinations

– Does the person hear voices that are not present in reality?	☐ *yes* ☐ *no*	dk
– How much do the voices urge the person to be harmed or endangered? . . .	min low medium high max: 0 1 2 3 4 5 6 7 8 9 10	dk
– How much do the voices urge the person to harm/endanger other people? .	0 1 2 3 4 5 6 7 8 9 10	dk
– How likely is it that the person will act on the voices?.	0 1 2 3 4 5 6 7 8 9 10	dk

Questions on paranoid delusions

– Does the person suffer from delusions (ie clearly incorrect and illogical ideas about his or her life and circumstances)? . . . . ☐ *yes* ☐ *no* ☐ dk

min low medium high max

How much is the person obsessed about the perceived bad behaviour of particular known people? . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

How much is the person obsessed about being harmed or persecuted by particular known people? . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– How likely is it that the person will act on any delusions? . . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

Further questions on mental faculties/cognitive capacity

– Does the person have impaired cognitive functions (thinking processes, memory, concentration) or dementia? . . . . ☐ *yes* ☐ *no* ☐ dk

min low medium high max

– To what extent have the thinking processes and memory deteriorated? ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– How poor is the person's ability to concentrate? . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– To what extent do you believe the person to have learning disabilities? ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

Further questions on personality

– How assertive is the person? . . . . ☐ *not assertive* ☐ *somewhat assertive* ☐ *normally assertive* ☐ *very assertive* ☐ *excessively assertive* ☐ *dk*

min low medium high max

– How much does the person lack empathy? . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

To what extent is the person overdependent (weak, over-reliant on others, easily influenced, unable to function independently)? . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– How organised is the person's general approach to life? ☐ *chaotic* ☐ *disorganised* ☐ *normal* ☐ dk ☐ *very organised* ☐ *obsessional/perfectionist*

min low medium high max

– How much does the person lack the ability to cope with major life stresses? ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– How hostile is the person? . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– How impulsive is the person? . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– How unreliable is the person (eg untrustworthy, unpredictable, shiftless)? ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

Further questions on motivation and engagement with world

– How much is the person physically isolated from the world? . . . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– How much has the person mentally disengaged or withdrawn from the world? ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– To what extent does the person lack motivation in general life? ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

– To what extent does the person appear listless or lacking energy and drives (eg loss of enthusiasm, libido, and/or interest)? . . . . ☐0 ☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7 ☐8 ☐9 ☐10 ☐dk

Further questions on social context

Questions on current relationships

– Are you concerned about risks due to the person's current relationships? ☐ *yes* ☐ *no* dk ☐

– How much does the person lack an external network of relationships? min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– How much does the person lack supportive relationships? ……. 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person have detrimental relationships (eg bullied, over-protected) or ones with people who have antisocial or exploitative behaviours? . . 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person perceive his or her relationships to have recently changed for the worse (eg bitter divorce or separation; rows; carer's role; bereave- ment)? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

Questions on living arrangements

– Are you concerned about risks due to the person's living arrangements? . . . ☐ *yes* ☐ *no* dk ☐

– How often does the person's living place change? . ☐ *monthly or more* ☐ *several times per year* ☐ *every year* ☐ *less* ☐ *dk*

– What type of supported living does the person have . . . ☐ *institution/fully supervised* ☐ *daily support* ☐ *limited support* ☐ *no support (own home)* ☐ *hostel* ☐ *homeless* dk ☐

– To what extent is the person's accommodation isolated from other living abodes and resources? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the neighbourhood or care environment exacerbate the person's particular risks (eg violent, easy access to drugs and unhelpful temptations)? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent is the person's accommodation showing lack of care? . .. 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent does the person think the accommodation is unfit to live in? . 0 1 2 3 4 5 6 7 8 9 10 dk

Questions on financial problems

– Are you concerned about risks due to financial problems? . . .. ☐ *yes* ☐ *no* dk ☐

– How anxious is the person about perceived levels of debt? . . . . .. min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent does the person's income fail to meet the basic essentials for supporting living requirements of the household (food, rent, heating, etc)? 0 1 2 3 4 5 6 7 8 9 10 dk

Questions on employment

– Are you concerned about risks related to the person's employment or lack of it . ☐ *yes* ☐ *no* dk ☐

How unstable is the person's employment history (eg always changing, poor disciplinary record)? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person believe a recent change in employment to be detrimental (eg loss of job, retirement, work stress)? 0 1 2 3 4 5 6 7 8 9 10 dk

Further questions on general current behaviour

To what extent does the person take reckless risks (eg with sexual behaviour, driving, gambling and other leisure pursuits)? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent does the person's behaviour lead to unintentional risks (eg fire or harm due to being careless, thoughtless or forgetful; self-injurious behaviour)?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person experience problems with sleeping?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent has the person been behaving out of character or unpredictably in recent weeks?	0 1 2 3 4 5 6 7 8 9 10	dk
To what extent does the person display challenging behaviour (eg antisocial, disruptive, resistance to advice, predatory)	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person's day lack any structure?	0 1 2 3 4 5 6 7 8 9 10	dk
– What is the person's general level of activity?	☐ passive/inert ☐ underactive ☐ normal ☐ overactive ☐ hyperactive	dk

Further questions on substance misuse

	min low medium high max	
– To what extent does the person misuse alcohol to the detriment of his or her life? ..	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person misuse drugs to the detriment of his or her life?	0 1 2 3 4 5 6 7 8 9 10	dk

Further questions on insight and responsibility

To what extent does the person lack insight into the potential consequences of his/her risk-taking behaviour?	0 1 2 3 4 5 6 7 8 9 10	dk
To what extent does the person lack any sense of responsibility for the outcomes of risk-taking behaviour?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person fail to recognise any need for help with mental- health issues?	0 1 2 3 4 5 6 7 8 9 10	dk

Further questions on physical health problems

If the person has a life-threatening or degenerative illness (eg cancer, multiple sclerosis, Parkinson's, emphysema, HIV), when was it first diagnosed?	d m y	dk
	min low medium high max	
– To what extent does the person suffer from chronic or periodic pain?	0 1 2 3 4 5 6 7 8 9 10	dk
To what extent does the person suffer from problems that affect mobility and/or dexterity (eg eyesight, balance, disability due to disease or trauma)?	0 1 2 3 4 5 6 7 8 9 10	dk
– To what extent does the person suffer from physical problems affecting communication?	0 1 2 3 4 5 6 7 8 9 10	dk
To what extent has there been a deterioration in physical health over the last few months, including temporary or cyclical problems? .	0 1 2 3 4 5 6 7 8 9 10	dk

Further questions on concordance with health services/medication/therapies

To what extent is the person failing to concord with medication or therapies, either deliberately or due to complexity of polypharmacy, for example?	0 1 2 3 4 5 6 7 8 9 10	dk
To what extent does the person fail to perceive health or social care services as supportive?	0 1 2 3 4 5 6 7 8 9 10	dk
– When did the person last access any health or social-care services or have ongoing medication reviewed?	d m y	dk
	min low medium high max	
To what extent does the person and/or carer believe that their medication/therapies – are failing to have a beneficial effect?	0 1 2 3 4 5 6 7 8 9 10	dk

Further questions on adverse life events

– Has the person ever been the victim of any form of abuse (eg physical, sexual, financial, emotional)? . . . . ☐ yes ☐ no ☐ dk

– Has the person ever been sexually abused? . . . . ☐ yes ☐ no ☐ dk

– When was the most recent episode of sexual abuse? . . . . ☐ d ☐ m ☐ y ☐ dk

– Was the first episode of sexual abuse during childhood or early adolescence? . ☐ yes ☐ no ☐ dk

– Has the person ever been physically abused? . . . . ☐ yes ☐ no ☐ dk

– When was the most recent episode of physical abuse? . . . . . ☐ d ☐ m ☐ y ☐ dk

– Was the first episode of physical abuse during childhood or early adoles- cence? . . . . ☐ yes ☐ no ☐ dk

– Has the person ever been emotionally or racially abused? . . . . . . ☐ yes ☐ no ☐ dk

– When was the most recent episode of emotional or racial abuse? . ☐ d ☐ m ☐ y ☐ dk

– Was the first episode of emotional or racial abuse during childhood or early adolescence? . . . . ☐ yes ☐ no ☐ dk

– Has the person ever been financially abused? . . . . ☐ yes ☐ no ☐ dk

– Has the person ever faced serious criminal justice proceedings (court cases, custodial sentences, etc)? . . . . ☐ yes ☐ no ☐ dk

– To what extent did the person grow up in emotionally disturbed or disruptive envi- ronments? . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– How seriously has the person suffered from eating disorders in the past? 0 1 2 3 4 5 6 7 8 9 10 dk

– How much has the person had detrimental educational experiences? . 0 1 2 3 4 5 6 7 8 9 10 dk

Further questions on person's behavioural presentation during assessment

– Are you concerned about the person's engagement with the assessor?. ☐ yes ☐ no ☐ dk

– How difficult is it to have rapport and empathy with the person? .. min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent is the person unwilling to communicate or respond to questions? 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent do you have an uneasy 'gut' feeling about the person (eg about the person's honesty, something doesn't quite add up, something missing)? . . . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

– Are you concerned about verbal indicators of risk? . . . . ☐ yes ☐ no ☐ dk

– How aggressive/hostile is the person's tone of voice? . . . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– How depressed and downbeat is the person's tone of voice? . . . . 0 1 2 3 4 5 6 7 8 9 10 dk

– To what extent is the person failing to make sense (eg incoherent, irrational)? . . . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

– Are you concerned about the person's body language and expression? . ☐ yes ☐ no ☐ dk

– To what extent does the person's body language indicate distress? . min low medium high max 0 1 2 3 4 5 6 7 8 9 10 dk

To what extent do the person's movements, posture, and facial expression indicate a low, downbeat, or gloomy mood? .... 0 1 2 3 4 5 6 7 8 9 10 ☐ dk ☐

– How aggressive or threatening are the person's movements and posture? .... 0 1 2 3 4 5 6 7 8 9 10 ☐ dk ☐

– To what extent does the person appear detached or preoccupied? .... 0 1 2 3 4 5 6 7 8 9 10 ☐ dk ☐

– To what extent does the person avoid eye contact? .... 0 1 2 3 4 5 6 7 8 9 10 ☐ dk ☐

– What is the person's predominant form of eye movement? . ☐ *unresponsive/glazed* ☐ *normal* ☐ *darting* dk ☐

How inconsistent are the person's physical, verbal, and emotional presentations (lack of congruence)? .... **min low medium high max** 0 1 2 3 4 5 6 7 8 9 10 ☐ dk ☐

Further questions on appropriateness of diet

– To what extent does the person fail to eat appropriately? .... 0 1 2 3 4 5 6 7 8 9 10 ☐ dk ☐

– Is the person's weight a cause of concern? Tick the appropriate description. .... ☐ *extreme underweight* ☐ *underweight* ☐ *weight OK* ☐ *overweight* ☐ *extreme overweight* dk ☐

– How much has the person experienced weight change in recent months? **min low medium high max** 0 1 2 3 4 5 6 7 8 9 10 ☐ dk ☐

– To what extent does the person fail to drink adequately? .... 0 1 2 3 4 5 6 7 8 9 10 ☐ dk ☐

Form completed by:

Setting (where completed): Date: ☐ *d* ☐ *m* ☐ *y*

Instructions for completing the form

1. This tool records your risk judgements associated with the person's mental-health problems and the information supporting them. It is *not* an interview schedule: *it is your prerogative how and when to ask questions*.
2. Rapid screening questions are placed first in the document, with an arrow pointing to the page number, *p*, where additional questions can be found for the screening question (e.g. *p4*). Relevance of information varies across assessments and further data is only required for screening questions that have been given a "yes" response. However, by answering all screening questions, GRiST will have recorded your comprehensive consideration of risk issues irrespective of how much information is actually supplied.
3. GRiST helps you record data only for those issues relevant to the particular circumstances and context of the current assessment. It has a number of questions that ask whether you are concerned about a concept or whether the concept applies and you only need to answer the questions indented beneath if your answer is *yes*.
4. Many questions have a ten-point rating scale to record your subjective judgement about the extent to which the item applies to the person. Response choices range from 0 for no extent, to 10 for maximum extent, with labels above the boxes to help interpret the meaning of the numbers. *Do not worry about the exact number: the ten-point scale allows for a margin of error and you are only expected to give a response that "feels right".*
5. Give dates as accurately as you can but leave the days and/or months blank if unknown.
6. If items were considered during assessment but no answer was obtained, mark the *dk* box for "Don't Know".

Repeat assessments using the paper form

If people are using GRiST on paper rather than the online version, then carrying out repeat assessments is inefficient because much of the data that has not been changed needs to be put in again on a new form. We have tried to help with this by providing a *repeat assessment* form on the following two pages. Detach it from the full form, print as many copies as you like, and follow the instructions for how to identify changed information on the full GRiST form.

Repeat assessment form for GRiST

Each item of information on this repeat-assessment form equates to a screening question on the full form and is in the same order. All you need to do is:

1. choose a different coloured pen or some other form of identification that distinguishes the repeat data from the data on the original GRiST form;
2. tick those questions on this repeat form where the repeat assessment has identified a change in status and fill in the changed data on the original GRiST form using the chosen distinguishing pen/mark;
3. in the space provided at the end of the repeat assessment, record the name of the repeat assessor, the date, and how the new GRiST data will be identified;
4. attach the repeat assessment form to the original GRiST assessment.

Please note that the online version of GRiST automatically accounts for historical and persistent data, making the han- dling of repeat assessments and the reporting of changes very much easier.

Repeat assessment questions

For all the risk areas below, state whether the repeat assessment has changed their data. If so, add the new data to the original GRiST form as instructed above.

SUICIDE	**Data changed?**
Past and current suicide attempts? *If yes, → p6*	☐ *yes* ☐ *no*
Current intention to commit suicide? *If yes, → p6*	☐ *yes* ☐ *no*
Potential triggers for prospective suicide? *If yes, → p7*	☐ *yes* ☐ *no*
Suicidal ideation? *If yes, → p7*	☐ *yes* ☐ *no*
SELF-HARM	**Data changed?**
Past and current episodes of self-harm? *If yes, → p7*	☐ *yes* ☐ *no*
Potential triggers for prospective self-harm? *If yes, → p7*	☐ *yes* ☐ *no*
Self-harm ideation? *If yes, → p8*	☐ *yes* ☐ *no*
HARM TO OTHERS OR DAMAGE TO PROPERTY	**Data changed?**
Past and current episodes of harm or damage? *If yes, → p8 but also record the most important information below*	☐ *yes* ☐ *no*
Targets of harm to others?	☐ *yes* ☐ *no*
Any violent assault/physical abuse? *If yes, → p8*	☐ *yes* ☐ *no*
Any fire-setting? *If yes, → p8*	☐ *yes* ☐ *no*
Intention for harm or damage? *If yes, → p9*	☐ *yes* ☐ *no*
Potential triggers for prospective harm or damage? *If yes, → p9*	☐ *yes* ☐ *no*
Ideation about violence? *If yes, → p9*	☐ *yes* ☐ *no*
Child protection issues?	☐ *yes* ☐ *no*
SELF NEGLECT	**Data changed?**
Appearance indicators of self neglect? *If yes, → p10*	☐ *yes* ☐ *no*
VULNERABILITY OF SERVICE USER	**Data changed?**
Falls? *If yes, → p10*	☐ *yes* ☐ *no*
Person's appearance and behaviour indicators of vulnerability? *If yes, → p10*	☐ *yes* ☐ *no*
RISK TO DEPENDENTS?	**Data changed?**
Any new information affecting risks to dependents? *If yes, → p5* . . .	☐ *yes* ☐ *no*

GRiST

www.galassify.org/grist patient name/id:

SCREENING QUESTIONS RELEVANT TO MORE THAN ONE RISK

	Data changed?	
Feelings/emotions? *If yes, → p11*	☐ *yes*	☐ *no*
Person's perspective of self worth? *If yes, → p11*	☐ *yes*	☐ *no*
Mental health problems? *If yes, → p11*	☐ *yes*	☐ *no*
Mental faculties/cognitive capacity? *If yes, → p12*	☐ *yes*	☐ *no*
Personality? *If yes, → p12*	☐ *yes*	☐ *no*
Motivation and engagement with world? *If yes, → p12*	☐ *yes*	☐ *no*
Social context? *If yes, → p13*	☐ *yes*	☐ *no*
General current behaviour? *If yes, → p13*	☐ *yes*	☐ *no*
Substance misuse? *If yes, → p14*	☐ *yes*	☐ *no*
Insight and responsibility? *If yes, → p14*	☐ *yes*	☐ *no*
Physical health problems? *If yes, → p14*	☐ *yes*	☐ *no*
Concordance with health services/medication/therapies? *If yes, → p14*	☐ *yes*	☐ *no*
Adverse life events? *If yes, → p15 Consider also social context (p.13) and physical health (p.14).*	☐ *yes*	☐ *no*
Person's behavioural presentation during assessment? *If yes, → p15*	☐ *yes*	☐ *no*
Appropriateness of diet? *If yes, → p16*	☐ *yes*	☐ *no*

REPEAT RISK SUMMARY

	0	1	2	3	4	5	6	7	8	9	10	dk
Suicide	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Self harm	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Self neglect												☐
Harm to others /damage	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Vulnerability	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Risk to dependents	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

OVERALL RISK COMMENTS

UPDATED ACTIONS

Form completed by:

Method used to distinguish repeat assessment data:

Setting (where completed): Date: *d* ☐ *m* ☐ *y* ☐