Socio-Technical Perspective on Managing Type II Diabetes

Full Paper

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Abstract

Social attributes such as education level, family history or place of residence all place a strong role in the probability of a person developing type II diabetes later in life. The aim of this paper is to develop a knowledge system based to use social attributes to estimate the prevalence of type II diabetes in a given area in Australia to support public health policymaking. The focus of this paper is towards answering the research question How can social determinants associated with type II diabetes, be used to incrementally develop a supporting knowledge-based system (KBS)? The contribution of this paper is two folds: 1. The problem domain is analysed and a suitable KBS development framework is chosen 2. A prototype is developed and presented. Initial results with preliminary data confirm the validity of the approach.

Keywords: Social Determinants, Type II Diabetes, Decision Support Systems, Knowledge-Based Systems, Ripple Down Rules

1 INTRODUCTION

The epidemic of type II diabetes is growing globally. It affected 366 million people in 2011 (Sim et al. 2017) and this is expected to increase to 552 million people by 2030 (Sim et al. 2017). Here in Australia diabetes costs the nation an estimated $14.6 billion annually (2015a). This was a considerable rise from the $10.6 billion (Lee et al. 2013) in 2005. In the same timeframe, Australia had spent $161.6 billion on health (2016). This indicates that just under 10% of the Australian Government's Health expenditure is spent on diabetes. The numbers above indicate a significant cost to the Australian people, as indeed the world at large. This would indicate that there's significant evidence to suggest that working on better ways of dealing with and managing type II diabetes would be of benefit.

Social determinants are a set of conditions that a person is born into, lives within and conducts his/her normal activities within. These include but not limited to, lifestyle, education level, culture and poverty etc. During a person's life, some people manage to change their social determinants others are confined within the one that they were born into for the duration of their natural life (2018a).

Type II diabetes means that a person's pancreas is no longer producing enough good insulin. In other words, the body has built a resistance to it. It's a chronic condition that develops over years (2019).

The question that the paper focusses on is "How can these social determinants be used to develop a Knowledge-Based System (KBS) incrementally"? As the research involves predictive analysis, some widely accepted predictive techniques were examined and compared for suitability for the task at hand. As a result of the literature review and liaison with the various academic & industry experts in predictive analysis techniques, four available Knowledge-Based Development techniques were chosen for further investigation. They are Artificial Neural Networks (ANN), Bayesian Networks, Markov Networks and Ripple Down Rules (RDRs).

The expected users of the proposed decision support system (DSS) are health insurance companies, life insurance companies etc., government ministers and their advisors etc., It is likely that many of those users have limited IT skills. Hence, in order to maximise the DSS's effectiveness, a socio-technical approach is used rather than a purely technical one. An appropriate Human-Computer Interface (HCI) must be considered in the development of the DSS. That is the communication between system and users (Sommerville and Dewsbury 2007) is a central consideration in the design decisions of the DSS. A social-technical perspective also addresses the challenge of constellation users from the various organisations and/or departments consolidated for a more integrated care delivery (Dessers et al. 2019). A most salient consideration in our application is that the contributors of domain knowledge cannot be expected to be able to program when they communicate their knowledge to the system. We also anticipate the knowledge is constantly liable for change so such users cannot be burdened with coding or programming effort when s such, the proposed KBS & DSS that the domain expert isn't required to have a lot of technical skills to develop and maintain the KBS required to drive the DSS.

Taking the above into account, the research approach is unique in two ways. Firstly, to develop the KBS during the knowledge acquisition phase not afterwards as is common. Secondly, the very nature of RDRs, the selected DSS development technique forces the subject matter expert to explain any discrepancies in the data for similar cases leading to different conclusions.

2 LITERATURE REVIEW

Social determinants have an effect on other health conditions/issues as well as diabetes Sauliune and Kalediene (2015), (Smith et al. 2016) and (Hill et al. 2013a). Some research has suggested that social determinants are associated with type II diabetes (Schwerdtle 2016). Whilst the literature also indicates that KBSs have previously been used in healthcare (Sim et al. 2017). This all supports the idea that social determinants could be used to develop a KBS. The exact determinants are not yet identified limiting data availability. The novelty of this research will be to develop the KBS incrementally. Therefore, an appropriate tool is required for the incremental development of the proposed KBS. These tools are discussed for their suitability as the framework for the proposed KBS. However, we first review the literature related to identifying the social determinants in the first place.

2.1 Social Determinants

Hill, Nielsen & Fox (2013) propose a sociobiological cycle of type II diabetes (Figure 1). That is, social determinants such as income, education, housing, and nutritious food access etc, lead to poor dietary choices. In turn, these factors then lead to inadequate lifestyle factors such as physical activity habits as well as primary health care access. Combined, these factors can affect a diabetic's work and/or education attainment productivity (Hill et al. 2013b). Further limiting a diabetic's ability to secure the resources required to gain suitable income streams to access better healthcare. Hence, the cycle continues. This process results in and contributes to adverse outcomes (Hill et al. 2013a). It may lead to the retardation in the progression rate of type II diabetes. The current interventions, covered under "Biological and Psychological Responses" in figure 1, refer to monitoring and controlling factors such as blood pressure and blood glucose levels etc. The social determinants of discussed above and indicated in figure 1 below, are not adequately addressed in managing a chronic condition such as type II diabetes (Hill et al. 2013b). These social determinants will continue to be a barrier to improving population health unless they are adequately addressed (Hill et al. 2013b).

This could be addressed at a policy level as Schwerdtle (2016) suggested. Therefore, it stands to reason that a system that can manipulate the various data from the various sources to provide useful and accurate information would be a handy tool for policymakers and their advisors. Hence, the purpose of a KBS in this area. Figure 1 suggests that there's currently a biological and psychological response to the disease, ie. a clinical perspective. However, figure 1 also suggests that more social response is required for the disease. This is in direct correlation with the current research, adding further justification. So far, the discussion has been establishing and utilising social determinants. This gives rise to the question of "Once the social determinates are established and utilised to develop a KBS how is the output used?"

Ramaprasad et al. (2016) discuss developing an ontological mapping of Australia's National Health Programs. The health programs discussed here are mapped onto an ontology with five dimensions. The five dimensions are: policy-scope, policy-focus, outcomes, type of care and population served (Ramaprasad et al. 2016). Hence, the purpose of this research and the proposed development of a KBS. In fact, the Ramaprasad et al. (2016) article discusses traditional policy analysis from various perspectives. These perspectives include policymakers, doctors and allied staff, etc. Namely being communicable diseases, maternal, child health and geographical location (Ramaprasad et al. 2016). What the article doesn't discuss is how to obtain this information and present it in a usable manner. Hence, the development of the proposed KBS would fulfil this gap.

There is research suggesting that particular dietary patterns are associated with type II diabetes (Galbete et al. 2018). (Galbete et al. 2018) conducted research on associations between Ghanaian adults' dietary patterns and type II diabetes. They concluded that the various diets of Ghanaian adults were inversely associated with type II diabetes. This indicates that dietary habits are social determinant that could be used in this research. Galbete et al. (2018) and Schwerdtle (2016) suggested that particular diets are associated with type II diabetes. Diabetes Australia, Petersen et al. (2011), Gurka Filipp and Debor (2018) suggested a link between type II diabetes and geographic regions. These two findings could be combined by establishing the normal dietary patterns of people living in particular regions, which could be viewed as a composite social determinant. The determination of this social determinant could be done with the aid of the proposed KBS will be discussed next.

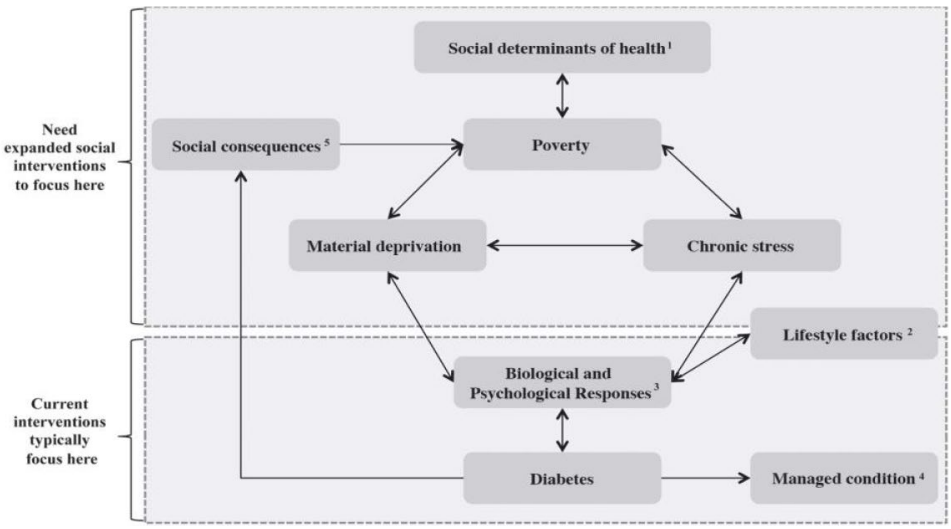

Figure 1. The sociobiological cycle of diabetes. Source: Hill, Nielsen & Fox (2013)

Schwerdtle (2016), discusses the social determinants of health, in particular, type II diabetes. The article discusses reducing the risk of diabetes is about addressing the social determinates that could lead to its onset. Schwerdtle (2016) suggests that type II diabetes could also be combated by policymakers and should be "addressed at a policy level". Schwerdtle (2016) lists a few social determinants associated with type II diabetes but discusses more the importance of addressing them. Schwerdtle (2016) does mention how social determinates of health are economic, social and political systems do shape the conditions of daily life, but not the specific ones that could be associated with type II diabetes. Schwerdtle (2016), suggests a strong emphasis on education in conjunction with strategies to promote a healthier lifestyle, incorporating more exercises and healthier food, etc. Schwerdtle (2016) also suggests that nurses are well placed to advocate for these changes to occur.

Petersen et al. (2011) discuss the potential of a geodemographic system for targeting particular neighbourhoods for health issues. The system was the London Output Area Classification (LOAC), which was then compared to six other systems from various sources, both government and commercial (Petersen et al. 2011). This classified people on the basis of where they lived in order to decide where to allocate the various healthcare resources. Evidence of the geographic aspect of type II diabetes can be seen on the Diabetes Australia website. The diabetes Australia website has a diabetes risk calculator to provide a person with the probability of developing type II diabetes within the next 5 years. This risk calculator works by asking 11 short questions (2015b). As part of this research, the authors conduct a short experiment on a diabetes risk calculator. The Diabetes Australia risk calculator findings were that a person born in the Middle East has a much higher chance of developing type II diabetes than a person born in Australia (2015b). This provides further evidence that geographic location plays a role in the onset of type II diabetes. This suggests that perhaps future research could include incorporating the KBS developed in the course of this research with a Geographic Information System (GIS). Geographic location has also been flagged as a potential social determinant that has a correlation to Metabolic Syndrome (MetS) in the US (Gurka et al. 2018). MetS is a collection of disorders that increase the risk of type II diabetes and other diseases (2018b). Gurka, Filipp and Debor (2018) made adjustments for the variation in sexes, age groups and ethnicities in various locations in the US. The findings were that the prevalence of MetS was >= 35% in West North Central, West South Central, and East South Central whilst 30% in the Pacific, New England, and Mid-Atlantic areas (Gurka et al. 2018).

2.2 Knowledge-Based Systems (KBS) & Decision Support Systems (DSS)

A Knowledge-Based System (KBS) reduces a large body of domain knowledge down to a set of rules and facts (Gaines and Shaw 1993). Knowledge-based systems are developed by a knowledge expert, sometimes referred to as a *knowledge engineer*, working closely with the domain expert to elicit domain knowledge into an appropriate structure to ensure an acceptable performance by the KBS. This is done through a diverse range of activities as indicated in figure 2 below (Gaines and Shaw 1993).

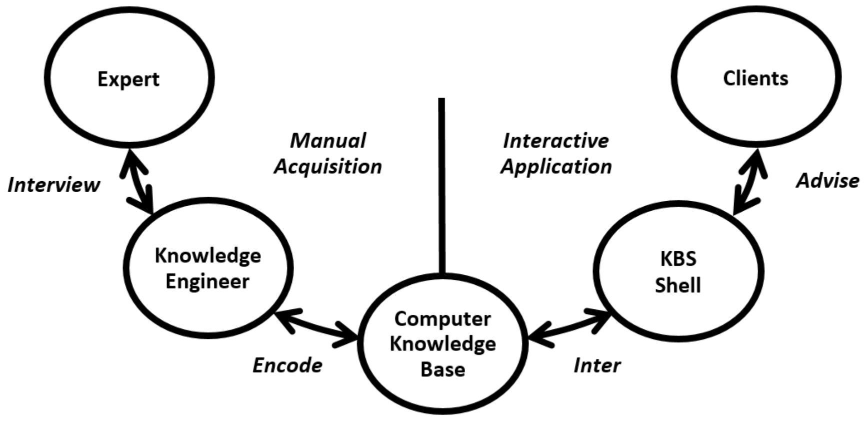

Figure 2. The basic knowledge Engineering. Source: Gaines & Shaw (1993)

The rules and facts referred to earlier, are then fed into a Decision Support System (DSS) to make inferences about particular cases. The process in figure 2 can be broken down into the following steps (Gaines and Shaw 1993):

1. The knowledge engineer works closely with the domain expert to elicit their knowledge;
2. The knowledge engineer then encodes the extracted knowledge for the knowledge base;
3. The shell then utilises the knowledge base to obtain inferences regarding particular cases and these inferences are used to obtain advice on particular cases.

The essence of a DSS is to maximise the effectiveness of decision-makers (Vogel 1985). DSSs are not designed to replace decision-makers, but to support their decisions (Vogel 1985). In the absence of adequate supporting tools, the structure of large databases and content may overwhelm decision-makers (Vogel 1985). The knowledgebase provides that structure and supportive tool.

The process of decision making involves 3 phases (Vogel 1985):

1. Intelligence, that is searching for a condition suitable for a condition;
2. Design, that is, determining a possible course of action; and
3. Choosing the appropriate course of action.

KBSs and DSSs have often been used in healthcare, but not in a population health management perspective. The KBS sought here would then be used by policymakers. This would play a significant role in reducing the above-mentioned costs and impact associated with type II diabetes along with social impact, both within Australia and around the globe.

Clearly, there's work being conducted regarding utilizing social determinants to address and manage type II diabetes around the globe (Hill et al. 2013a); Kalediene and Sauliune and Kalediene (2015); and (Schwerdtle 2016). In recent research, it was established that adverse pregnancy outcomes are more common among Aboriginal and Torres Strait Islander women than non-indigenous women (Gibson-Helm et al. 2018). It was also established that later in life expectancy of Aboriginal and Torres Strait Islander women varied from non-indigenous women due to non-communicable diseases (NCDs) (Gibson-Helm et al. 2018). Using continuous quality improvement (CQI), various social determinants were identified as barriers to high-quality health care to Aboriginal and Torres Strait Islander women in Australia (Gibson-Helm et al. 2018). Four primary barriers identified were smoking, alcohol, psychosocial wellbeing and nutrition. Also using CQI Gibson-Helm et al. (2018) also identified priority evidence-practice gaps in Aboriginal and Torres Strait Islander maternal health care (Gibson-Helm et al. 2018). Various strategies were then developed to address these findings. They include upskilling health staff, advocating healthy food and partnering with communities on health promotion projects, etc.

Other research has been conducted on social determinants associated with various health conditions. For example, research has been conducted developing a toolkit that helps health workers to ask their patients about their social determinates of health and consequently referring them to non-clinical support resources (Naz et al. 2016). There have been conferences on discussing the various cross-cultural social determinants and how these could be used to implement healthcare KBSs. However, due to the size constraints of this paper, these will not be discussed now. It suffices to say that they are further evidence of the importance of social determinants used to develop health care KBSs.

However, the exact social determinants associated with type II diabetes are not fully understood. It is anticipated that some of these determinates may be revealed whilst this research is in progress. Hence, the IS tool required must be flexible enough to accommodate the incremental nature of information acquisition. That is, the KBS will be developed iteratively. Therefore, an incremental knowledge acquisition process is required for the proposed development of this KBS. Hence, the novel concept in this research.

Shukla et al. (2018) proposed a robust data analytical model to provide a better understanding of the factors associated with cancer patient survivability. The system comprised of a large data set used to identify patterns of survivability of cancer patients (Shukla et al. 2018). The work then proposed segmentation of patient historical data could be formulated into clusters and identifying patterns within these clusters. The appropriate course of action could then be taken to improve the patient's survivability. The system operates with little to no input from an expert (Shukla et al. 2018). In another health KBS, Sangi et al. (2015) developed a risk advisor model to predict the chances of type II diabetes complications with respect to changes in risk factors. This was done using regression analysis and Artificial Neural Networks (ANN) (Sangi et al. 2015).

3 KNOWLEDGE-BASED SYSTEMS DEVELOPMENT TECHNIQUES

As discussed by Hill, Nielsen & Fox (2013), there has been considerable biological and psychological intervention directed at managing type II diabetes. However, Hill, Nielsen & Fox (2013) suggests that there should be more of a focus on social interventions. That is, shifting the context into the public health domain, adding a new perspective in managing type II diabetes. As suggested by Hill, Nielsen & Fox (2013), this area requires more work. The difficulty is, that there is not a significant amount of this kind of data available in this domain, here in Australia. In fact, according to the NSW Ministry of Health, a lot of it does not exist (Taylor 2019).

That being the case, social determinants data availability is scarce and incomplete. Therefore, decisions are currently perhaps made on the basis of deep medical expertise. However, who are the people making these decisions? Doctors, researchers, healthcare professional etc. All of which rely heavily on clinical expertise. As suggested earlier, if the context is shifted to public health, there is a new set of decision-makers. These include health insurance companies, statisticians, other researchers, and various politicians etc. However, as discussed by the NSW Ministry of Health (Taylor 2019), this kind of data is scarce and limited. As they're not sure about the knowledge, decision-makers using this data have limited ability to make decisions. As it's a domain that still requires more work (Hill et al. 2013b), they're likely to make various assumptions till validated by actual data. This may be pertinent to test the limit of the incremental development approach.

Most predictive analysis methods such as Artificial Neural Networks (ANNs), Bayesian Networks and Markov Networks, etc., require an abundance of data. They use this data to look for patterns and trends in the data for the purpose of predicting future outcomes. As discussed earlier, such data on social determinants associated with type II diabetes are scarce and limited. Therefore, what's required is a predictive analysis method capable of incremental development due to the current absence of available data. Ripple Down Rules (RDRs) does have those capabilities and is well suited to the incremental development technique. RDRs will be discussed further in the following section.

4 RIPPLE DOWN RULES (RDRs)

RDRs knowledge base development relies on updates based on knowledge from an expert (Galani et al. 2015; Beydoun and Hoffmann 2000). The resultant product is a collection of an interconnected set of rules organized in a binary tree structure where every node has 2 branches, a "True" and a "False" branch (Beydoun and Hoffmann 2000; Beydoun and Hoffmann 2001). Based on expert feedback, particular rules written to satisfy cases traverse the binary tree to reach a node. The process works by selecting a case and comparing its condition to the expected condition. If "True" then the conclusion is "Default Conclusion". If the case returns a "False" comparison, then the last condition satisfied by a rule is returned to the knowledge base. This process begins at the root node and is repeated until reaching a leaf node (Beydoun and Hoffmann 2013). Assuming *t* to indicate a leaf node required, then 'rippling down' to *t* guarantees that at least the default rule is satisfied, hence, returning a conclusion. The RDR's update policies are based upon the concept that when a knowledge-based system makes an incorrect conclusion, a new rule *r* is added to correct the conclusion in the same context that the incorrect conclusion was made (Beydoun and Hoffmann 2013) (see Figure 3).

In an RDR KBS, rules are added only in the context of their desired application (Beydoun and Hoffmann 2013). Rules are added to satisfy a case for which the original sequence of rules failed, excluding cases covered by its predecessor rule (Beydoun and Hoffmann 2013). Rules are never removed or modified because the corrected case is actually in the newest added rule (Beydoun and Hoffmann 2013). Due to the way conditions of new rules are added, correction made by the expert is guaranteed to be valid (Beydoun and Hoffmann 2013). Should an expert disagree with a knowledge base conclusion, then the knowledge base has failed and requires modification. Hence the proposed monitoring during development concept. This modification can be carried out directly by the expert due to the simplicity of its modification (Beydoun and Hoffmann 2013). There are two main features of RDRs which formulate the simplicity of its modification. Firstly, that the cause of failure is automatically determined due to the knowledge base's tree-like structure. That is, a new rule is added to the leaf node and is attached to the last visited rule prior to the knowledge base's failure (Beydoun and Hoffmann 2013). Secondly, the knowledge base's framework ensures that every newly added rule is consistent with its corresponding new case, without creating any inconsistencies with previously classified cases. That is, each new rule added is justified for a case classified by the expert (Beydoun and Hoffmann 2013).

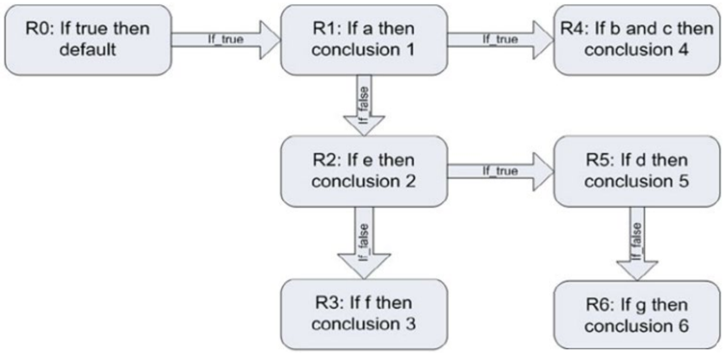

Figure 3. A classification RDR tree. A case to be classified starts at the root default node and ripple down to a leaf node. Source: Beydoun and Hoffmann (2013)

As our data required tends to come in subsets where uniform distribution is likely, ie. Assume 2 different people randomly selected in any given postcode will have the same probability of having type II diabetes. Hence, there is coverage but, very limited density and volume. The coverage is provided by the expert knowledge of the individual(s) developing each RDR (see figure 4).

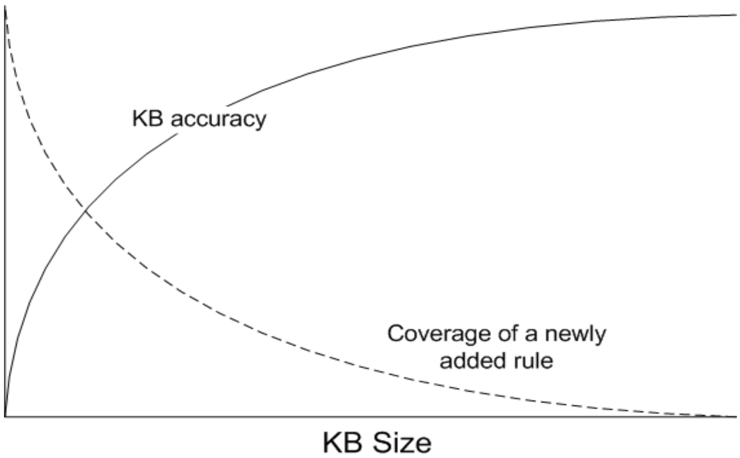

Figure. 4 RDR Convergence: added accuracy is diminished with size. The number of instances that individual rules classify drops quickly as the knowledge base converges. Source: Beydoun and Hoffmann (2000, 2001)

Predictive analysis techniques normally allow for discrepancies in conclusions based on datasets without offering any real explanation on the reason. For example, if you had a dataset said indicated a person over 50 years of age, born in the Middle East with a family history of type 2 diabetes and the conclusion of that person is a diabetic. In the same dataset, along comes a person with the same social determinants and the conclusion is that that person is not a diabetic. Most predictive analysis techniques would put that down to discrepancies in the dataset and often ignore it. However, the very nature of RDRs would force the subject matter expert to examine other social determinants to establish why this discrepancy occurred and develop a new rule to account for it. That is, unlike other predictive analysis techniques, RDRs force the subject matter expert to justify discrepancies in the dataset.

5 SUMMARY AND DISCUSSION

This paper has proposed an alternative way to deal with and manage the consequences of type II diabetes. It discussed the Australian Government's national expenditure and other statistics from around the globe on the disease. It further explores possible social as well as the financial impacts of the disease. This notion is supported by citing the various articles from researchers around the world making similar claims based on their research. The authors propose that a Knowledge-Based System to be used by policymakers would be a beneficial tool in better utilization of the limited available resources. This, in turn, would lead to a reduction of the above-mentioned government expenditure on type II diabetes. Not to mention improving other social implications of type II diabetes.

Four common techniques are discussed for suitability as the framework for the proposed KBS. They are ANNs, Bayesian Networks, Markov Network, and RDRs. Results of this review are shown in Table 1. As discussed earlier, ANNs operate by comparing known variables with unknown variables in large datasets. Bayesian Networks operate by a series of probabilities with conditions sourced through large datasets. Similar to Bayesian Networks, Markov Networks also require large datasets and require some complex probability knowledge. All these techniques use various validation techniques through their respective large dataset. RDRs operate by traversing a decision tree during the data acquisition phase. Validation using RDRs is also conducted during the data acquisition phase.

Requirement	**Analysis Model**			
	ANNs	Bayesian Networks	Markov Networks	RDRs
Easy to use by non-IT Professional	×	×	×	√
Requires minimum IT professional intervention for maintenance	×	×	×	√
Does not rely on large datasets	×	×	×	√
Provides validation during development	×	×	×	√
Contains built-in decision-making process	√	√	√	√
Reaches accurate decisions	√	√	√	√
Provide explanation for abnormalities in conclusion	×	×	×	√

Table 1. Analysis Model against Requirement

RDRs is the method that most closely aligns with the situation at hand. That is, firstly, not a lot of data is available on social determinants associated with type II diabetes, some social determinants will be determined either through this research and/or while this research is being conducted and/or even after the conclusion of this research. Hence the need for incremental development of the proposed KBS. Secondly, due to time constraints, data validation must be done quickly. Incremental development using RDRs allows data validation to be done during the knowledge acquisition process, eliminating the need to backtrack to validate acquired data. Ultimately, speeding up the development process. Finally, RDRs allow the update and maintenance of the KBS to be carried out by subject matter experts not IS experts. This is due to the lack of complex probability, clustering, and/or database knowledge required as in the other prediction methods. Leading to minimal intervention by IT expert, hence reducing operating costs to end-user.

Based on the above comparison, RDRs were chosen as the framework for the KBS. This decision is supported this suggestion by reference to other researchers using RDRs in the medical domain all around the globe, most of which are in a clinical sense. The authors propose that these concepts could be modified to the RDRs being utilized in the development of KBSs in a non-clinical perspective, that is, a population health perspective.

Using the above-mentioned RDRs a prototype Diabetes Decision Support System (DDSS) has been implemented. Using SQL & C Sharp, it provides an easy to use interface for domain experts to use.

Below are some screenshots of the DDSS indicating its ease of use with functionality.

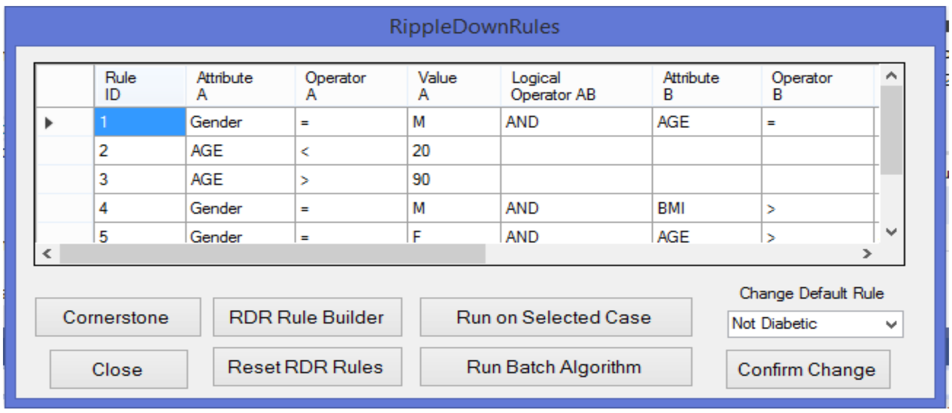

Figure 5. The RDR interface, providing domain users various options on their next course of action

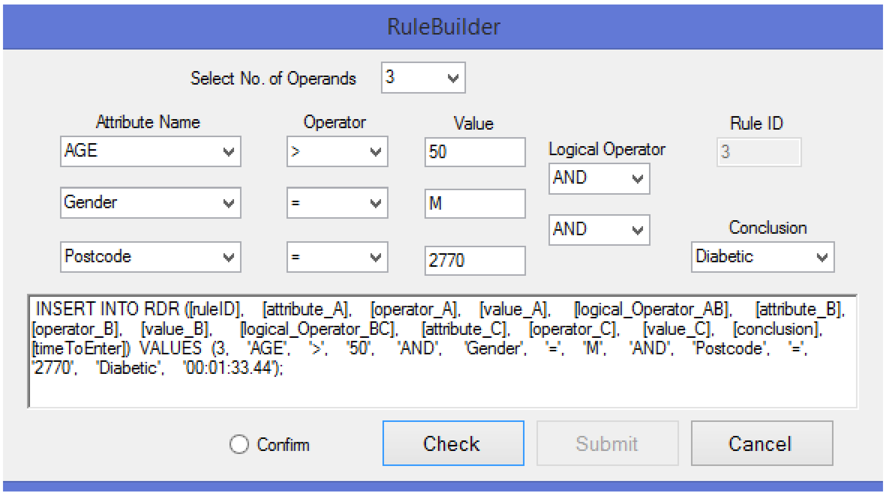

Figure 6. The rule builder interface, allowing domain users to construct rules to match cases and their own subject matter expertise

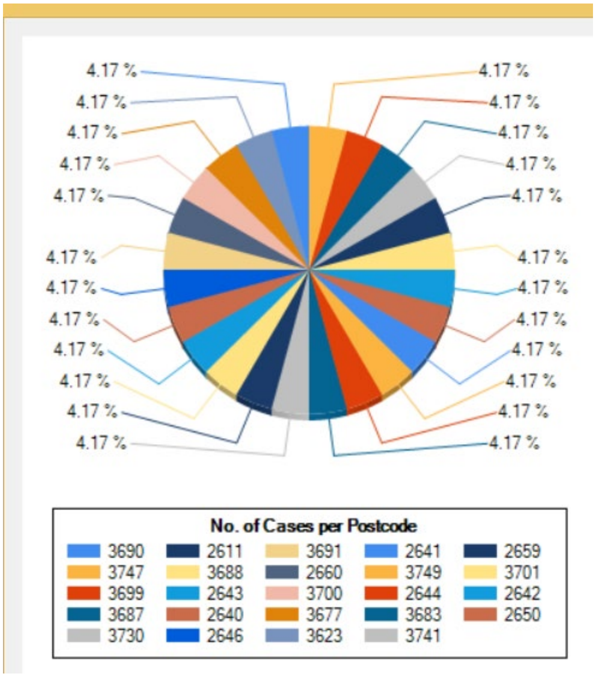

Figure 7. A graphical output display indicating the percentage of type II diabetes patients in a geographic region by postcode.

The DDSS is not yet complete. However, there are promising early signs. These signs indicate the apparent validity of the research.

6 CONCLUSION AND FUTURE WORK

This paper has proposed an alternative way to deal with and manage the consequences of type II diabetes. The research indicates that type II diabetes has major implications on society both financially and otherwise. It was also established that a lot of response from a clinical perspective, but not a lot from a social perspective (Hill et al. 2013a). This research aims to provide a tool to fill this gap.

Ripple Down Rules are proposed as the favoured method for developing a KBS to support policy development for type II diabetes management. This is due to two main characteristics of RDR: Firstly, there is a lack of available data about social determinants associated with type II diabetes. <removed for refereeing> proposed that in the absence of large data sets, the incremental development of a KBS was theoretically possible using RDRs. Secondly, the incremental nature of the data acquisition process lends itself to the constructed knowledge about this domain. Finally, the nature of RDRs forces the domain subject expert to justify any abnormalities in conclusions.

The next phase of the research is to complete the above-mentioned porotype DDSS. It's anticipated that data from various sources will be gathered and fed into the DDSS and analyse findings. Results of the DDSS will be further be analysed for validation the proposed theories discussed in this paper.

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Acknowledgements

The authors would like to acknowledgement emeritus professor Paul Compton (UNSW) for his assistance and support to Adel Omar during this research.