**CHAPTER TWO**

**2.0 LITERATURE REVIEW**

**2.1 EXPERT SYSTEMS**

Expert systems are a branch of applied artificial intelligence (3). An expert system is an intelligent computer program which captures the knowledge of a human expert (4). This information is then used to solve real-world problems in an automated fashion (5).The basic idea behind these systems is simply that expertise on a specific subject is transferred from a human to a computer(3). The main purpose of knowledge-based expert systems is to make the knowledge of a human expert and their experiences to be more commonly available, particularly in areas where they are not readily available(6). The quality, efficiency, and competitive control of expert system operations have increased over the years (4). Expert systems are applied in many different areas (1). In medicine expert systems are used to diagnose a medical problem and predict particular diseases (5), as well as to assist a physician in diagnosing medical problems of a patient or help interpret medical test results (4). Some of these systems are designed to train medical school students.

In chemistry expert systems are used to help interpret data from an experiment and they can assist in the planning and monitoring of the experiments and interpreting test data. They are very useful in determining molecular structures from mass spectrogram data (4). Whereas in computer science expert systems are used to assist in solving time consuming tasks (7). They are also used to design and diagnose a variety of computer systems (4).

**2.2 MEDICAL EXPERT SYSTEM**

In medicine, building and sharing knowledge about new theories, as well as advancing technologies and discoveries is of major concern (8). In this respect there is a need for physicians to be provided with efficient tools that offer target access to other knowledge such as medical statistics and expert opinions (8). Most medical expert systems applications are very useful for predicting and diagnosing a particular disease and providing recommendations regarding therapy and rehabilitation of the patient after therapy (5). They play a significant role where there are no medical experts available and in place where there is a shortage of hospitals, child health centers or dispensaries. However, medicine is a complex field and safety is a major issue. For this reason the lack of accuracy of information or systems can be a disadvantage (5). Medical expert systems play a significant role in providing support in common clinical problems like prediction of diseases, diagnosis of diseases, counseling of patients. All medical expert systems are in the form of a computer system (speech or text). The next section contains a brief description of three medical expert systems that played an important role in the success and development in the fields of expert systems.

**2.2.1 MYCIN**

MYCIN is a medical diagnosis expert system. It is designed to capture the expertise of a human expert on blood diseases (9). It is a rule-based system which uses production rules and backward chaining (9). It provides consultative advice to the user (physician or doctors) about the disease. It plays two main roles, namely identifying the most likely infectious diseases based on the patient’s medical data provided and suggesting a prescription or treatment (10). It consists of three sub-systems: Consultation system, Explanation system and Rule acquisition system (9). The following section highlights strengths and weaknesses of this medical expert system.

Strengths:

 Does not overlook or forget details

 It considers every possibility (10)

 It provides a set of acceptable solutions or conclusions

 It provides accurate and quick diagnosis (11).

Weaknesses:

 Each “clinical visit” means new data

 Correctness of conclusion is not guaranteed because it is based on heuristics, but it uses Turing’s test to judge correctness (10).

 Conciseness

 It is only available to diagnose infectious blood diseases (12).

 Bases advice on the data available at that particular time

 It does not follow up on previous decisions

Validity:

 It provides accurate and quick diagnosis (9)

 It operates using a simple inference engine and knowledge base system. Basically it will ask the user a set of yes/no queries. The program provides a list of possible diseases ranked from high to low based on the probability of each diagnosis. It then recommends drug treatment

**2.2.2 ONCOCIN**

ONCOCIN is a medical expert system tool that is designed to assist physicians in the treatment of cancer patients. It extends on the knowledge of MYCIN but provides high performance (13). Despite that it uses forward chaining; ONCOCIN uses the same rule-based approach as MYCIN. The main difference between the two systems is that MYCIN uses goal-driven reasoning process while ONCOCIN uses data-driven reasoning process. The main strength of ONCOCIN is that it allows an interaction with previous information or historical data but it requires inference rules based on assessment trends.

**2.2.3 DIAVAL**

DIAVAL is a medical expert system for the diagnosis of heart diseases and other kinds of data through echocardiography and other cardiac anomalies (7). In this system the diagnosis of a patient begins by registering personal information, medical history and other physical examinations. The information is placed in a blackboard (stores facts supplied by both the user and the system that can help solve the problem). The inference engine scans some of the rules while looking for matching patterns based on the query provided by the user. All matching rules will be added to the blackboard for further assessments (7).

**2.2.4 EMYCIN**

EMYCIN is known as ―Empty‖ MYCIN or ―Essential‖ MYCIN. EMYCIN is a goal direct backward-chaining RBR, as was MYCIN. When faced with a problem,

EMYCIN retrieves the list of rules whose conclusions affect the goal. For each of these rules, the premise is evaluated and conclusions drawn when true. In addition to the creation of an abstracted version of MYCIN, a number of tools have been added to the system to assist expert system architects build and debug. One of these tools is the abbreviated rule language (ARL). This language is an ALGOL like notation, rather than LISP or ― Doctorese‖ (the subset of English used by MYCIN). ARL is apparently easier to read than LISP and more concise than Doctorese. ARL is claimed to allow new rules to be included more easily than was previously possible with MYCIN. When a rule is entered, there is a syntactic check of the rule. This tool is designed so that the expert can concentrate on logical errors and omissions. There is also a limited semantic check. This compares the new or changed rule with existing rules that conclude about the same parameter, to ensure there are no contradictions or duplicate rules. Another tool that is included is a rule compiler. This tool transforms the rules of the system into a decision tree, which the compiler can compile into machine code. This eliminates the need for a rule interpreter.

**2.3. MEDICAL EXPERT SYSTEM IN RURAL AREAS**

Expert systems can assist a human expert in rural areas during the problem solving process (4). They are very useful in places with high numbers of health sector difficulties such as Nigeria (4). Most of these systems are applied in medical diagnosis, medical consultation and medical trainings.

**2.3.1 DIAGNOSIS**

These systems are very useful in places with poor living conditions as they can be integrated with multilingual speech recognition for patients who cannot read or write. Medical expert systems can help in medical diagnosis of patients (in hospitals), for minor diseases based on current conditions and the patient’s historical data. They can act in the place of a human expert (9) when they are not readily available.

**2.3.2 CONSULTATION SERVICES**

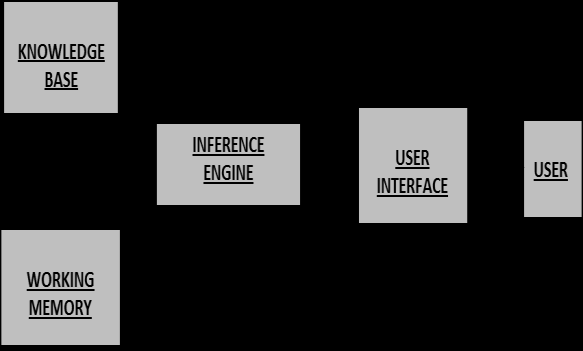
Medical expert systems can help to give advice to patients in rural areas; these systems can be applied for different people. For patients who cannot speak, for patient who cannot read or write, for patient who cannot see and so on, by providing speech-based and text-based applications.

**2.3.3 TRAINING**

These systems can be very useful in places where there is a lack of educational facilities (1). Expert systems are also used in places where there is a shortage of doctors or other trained personnel (12) and to help teach students, for example, medical student. These systems are utilized to help solve livelihood problems and can improve the lives of rural communities. (13)

**2.4. ARCHITECTURE OF AN EXPERT SYSTEM**

The fundamental structure of an expert system consists of four modules: Working memory, knowledge base, inference engine and a user interface (4). Other expert systems also consist of: Knowledge-acquisition (a process of acquiring, organizing and studying knowledge), an explanation module and a blackboard (7) instead of having working memory.



*Figure 1: Structure of an expert system*

Figure 1 above shows the structure of a medical expert system. Assuming the user interface acts as a physician or a patient, the user will answer a few questions about their conditions and the physician might need to add more medical data about a patient to help solve the problem.

**2.4.1** **THE KNOWLEDGE BASE**

The knowledge base is the heart of the expert system (5). It is the collection of facts and rules which describe all the knowledge about problem domain (4). It takes a collection of relevant knowledge that is stored in a computer and organizes the information in such a way that it can be used for inferences. These inferences are generally in the form of IF-THEN rules (5) that make use of various tests to rule in or out a diagnosis. These tests are scheduled based on suspicion of disease (14). Most of these systems are based on the concept of production rules (12), hence a rule is defined as “an IF-THEN” type structure which relates some known information contained in the “IF” part to other information. This information can then be concluded to be contained in the “THEN” part (4).

Example

*RULE 1:*

IF Battery is dead

THEN Car will not start

*RULE 2:*

IF Battery voltage is below 10 volts

THEN Battery is dead

These two rules capture knowledge which represents natural relationships for automobile diagnostics. However, Rule 1 relates the status of the battery to the status of the car and Rule 2 relates the status of the battery to its own status. Each rule is a separate declarative statement about the problem, allowing one to add rules to the system (4).

2.5 **DEPRESSION**

Depression is not just a form of extreme sadness. It is a disorder that affects both brain and body, including cognition, behavior, the immune system and peripheral nervous system. Unlike a passing sad mood, depression is considered a disorder because it interferes with ordinary functioning in work, school, or relationships. Unlike normal grief, which comes in waves, it is constant and oppressive. Depression also differs from ordinary mourning in that the mourner experiences the world as empty or bad, whereas clinically depressed individuals locate their sense of emptiness or badness in the self. (PDM Task Force, 2006, p. 109) Depression varies in intensity, from mild to extremely severe, and its symptoms can range from subtle to substantially disabling*.*

Affective symptoms include loss of pleasure and interest in life or activities the individual previously enjoyed (anhedonia); feelings of worthlessness, guilt, inferiority, inadequacy, helplessness, and weakness; and an overwhelming sense of sadness, despair, loss of hope, and self-hatred. Cognitive symptoms include impaired concentration and memory, indecisiveness, rationalization of guilt, and sustained and intense self criticism. Suicidal ideation of varying intensity is common in depressed individuals. Somatic symptoms are common among people with depression and can include fatigue, lethargy, sleep disruption (hypersomnia or insomnia), restlessness and agitation, headache, muscular pain, back pain, weight loss or gain (and associated appetite changes), and loss of sexual desire. A greater number and severity of somatic symptoms has been associated with treatment-resistant depression (TRD) (Papakostas et al., 2003).

**2.5.1 Subtypes of Depression:** *Anaclitic and Introjective Depression Subtypes.*

Sidney Blatt (1974) and a number of hiscolleagues identified two subtypes of depression: anaclitic and introjective depression. Blatt’s theories were based on a range of research into depression rather than being focused on symptoms, as are standard diagnostic systems*.* Instead, Blatt’s theories focused on the internal experience, preoccupations, and life experiences of individuals with depression.

They are primarily psychodynamic in nature, but his conceptions of anaclitic and introjective depression also correspond, respectively, to A.T. Beck’s (1983) subtypes of sociotropic and autonomous depression and are similar to Bowlby’s(1977, 1980, 1988) concepts of ambivalent and anxious attachment patterns.

Anaclitic depression is characterized by feelings of loneliness, helplessness, and weakness; the individual has intense and chronic fears of being abandoned and left

Unprotected and uncared for. Thus, these individuals have a desperate need to keep in close physical contact with need-gratifying others, and they experience deep longings to be loved, cared for, nurtured, and protected. Others are valued primarily for the care, comfort, and satisfaction they can provide because there has been little internalization of the experiences of gratification or of the qualities of the individuals who provided satisfaction. These dependent individuals rely intensely on others to provide and maintain a sense of well-being, and therefore they have great difficulty expressing anger for fear of losing the need gratification others can provide. Separation from others and loss are sources of considerable fear and apprehension, and are often dealt with by primitive means such as denial and/or a desperate search for substitutes (Blatt, 1974).

Introjective depression, in contrast, is characterized by self-criticism and feelings of unworthiness, inferiority, failure, and guilt. These individuals engage in constant and harsh self-scrutiny and evaluation and have a chronic fear of being disapproved and criticized, and of losing the approval and acceptance.

**2.5.2 Depression:** Patterns of Natural Course, Relapse, and Recovery

It is difficultto make accurate statements about the naturalcourse of depression because it is possible thatmany people experience depressions that, due to factors such as embarrassment and underreporting, are not identified in prevalence studies.The course of depression and prognostic indicatorsvary considerably according to type andnumber of previous episodes.

Symptoms of major depressive disorder (MDD) typically develop over a period of between several days and a number of weeks, although early indicators of an impending depressive episode (prodromal symptoms) can occur several months before the onset of a depressive episode that meets statistical standard of mental disorder (*DSM)* criteria.

The duration of a major depressive episode (MDE) is variable, although in many cases it is between 6 months and 2 years. Between 5-10% of all individuals continue to meet criteria for MDD for 2 or more years. Despite not meeting diagnostic criteria for MDD, it is probable that many people continue to experience depressive symptoms for a prolonged period of time (American Psychiatric Association, 1994). Forty percent of people will continue to meet diagnostic criteria 1 year after diagnosis of MDD, 20% will continue to have some symptoms without meeting full diagnostic criteria (partial remission), and 40% will have no mood disorder. Initial severity of the episode appears to be predictive

of its persistence, with more severe episodes lasting longer.

*DSM-IV* criteria for recovery from MDD are that the individual must not have met diagnostic criteria (i.e., depressed mood or loss of interest or pleasure plus four additional symptoms) for a period of 2 consecutive months. Throughout this time, an individual may still have a number of depressive symptoms, in

which case the individual is considered to be in partial remission.

*Relapse Rates.* A study by Piccinelli and Wilkinson (1994) found that 75% of people with MDD would have at least one further episode of depression within 10 years. Ten percent of patients in their study had experienced chronic and persistent depression for a period of 10 years. The *DSM-IV* states that approximately

50%-60% of individuals who experience a single MDE will go on to have a second episode. Individuals who have had two episodes have a 70% chance of having a third, and individuals who have had three episodes have a 90% chance of having a fourth. Clearly, the number of episodes is a predictor of the chance of recurring episodes of major depression. There is a greater likelihood of an individual

experiencing another episode of depression when there is only partial remission (i.e., some symptoms remain). While psychosocial stressors (such as relationship problems or bereavement) are often associated with the first or second episode, they are less often associated with subsequent episodes. People with dysthymia have a high probability of eventually having an MDE, with estimates as high as 79% of people with dysthymia going on to develop an MDD during their lifetime. People who have had an MDD and who have an underlying dysthymic disorder will also have a much higher rate of relapse for an MDD, with 62% experiencing an MDE within 2 years (Keller, Lavori, Endicott, Coryell, & Klerman, 1983).

2.5.3. Patterns of Symptomatic Recovery and Relapse *in Psychotherapy.*

In their study on patterns of symptomatic recovery in time-limited (cognitive-behavioral or interpersonal) psychotherapy conducted with a sample of 212 depressed patients, Barkham et al. (1996) found that percentages of patients meeting criteria for clinically significant change (measured by change from a distressed/symptomatic score to a non distressed/asymptomatic score on each of the 21 items of the Beck Depression Inventory; see A. T. Beck, Steer, & Brown, 1996; A. T. Beck, Ward, Mendelssohn, & Erbaugh, 1961) ranged from 34% to 89% within 16 sessions of therapy. In measurements of the 14 symptoms

(including guilt, crying, and pessimism) showing the fastest and largest change, between 50% and 89% of patients had achieved nondistressed/ asymptomatic scores on all items after 16 sessions of psychotherapy. Kopta, Howard, Lowry, and Beutler (1994) examined patterns of symptomatic recovery among a sample of 854 patients in ongoing (not time-limited) outpatient psychotherapy measured

using the Symptom Checklist-90 (SCL- 90-R) (Derogatis, 1983). The study identified three categories of symptoms: acute, chronic,

**2.6 ARTIFICIAL INTELLIGENCE**

From SIRI to self-driving cars, artificial intelligence (AI) is progressing rapidly. While science fiction often portrays AI as robots with human-like characteristics, AI can encompass anything from Google’s search algorithms to IBM’s Watson to autonomous weapons. Artificial intelligence today is properly known as narrow AI (or weak AI), in that it is designed to perform a narrow task (e.g. only facial recognition or only internet searches or only driving a car). However, the long-term goal of many researchers is to create general AI (AGI or strong AI). While narrow AI may outperform humans at whatever its specific task is, like playing chess or solving equations, AGI would outperform humans at nearly every cognitive task.

**2.6.1 WHY RESEARCH AI SAFETY?**

In the near term, the goal of keeping AI’s impact on society beneficial motivates research in many areas, from economics and law to technical topics such as verification, validity, security and control. Whereas it may be little more than a minor nuisance if your laptop crashes or gets hacked, it becomes all the more important that an AI system does what you want it to do if it controls your car, your airplane, your pacemaker, your automated trading system or your power grid. Another short-term challenge is preventing a devastating arms race in lethal autonomous weapons. In the long term, an important question is what will happen if the quest for strong AI succeeds and an AI system becomes better than humans at all cognitive tasks. As pointed out by I.J. Good in 1965, designing smarter AI systems is itself a cognitive task. Such a system could potentially undergo recursive self-improvement, triggering an intelligence explosion leaving human intellect far behind. By inventing revolutionary new technologies, such a super intelligence might help us eradicate war, disease, and poverty, and so the creation of strong AI might be the biggest event in human history. Some experts have expressed concern, though, that it might also be the last, unless we learn to align the goals of the AI with ours before it becomes super intelligent.

There are some who question whether strong AI will ever be achieved, and others who insist that the creation of super intelligent AI is guaranteed to be beneficial. At FLI we recognize both of these possibilities, but also recognize the potential for an artificial intelligence system to intentionally or unintentionally cause great harm. We believe research today will help us better prepare for and prevent such potentially negative consequences in the future, thus enjoying the benefits of AI while avoiding pitfalls.

**2.6.2 HOW CAN AI BE DANGEROUS?**

Most researchers agree that a super intelligent AI is unlikely to exhibit human emotions like love or hate, and that there is no reason to expect AI to become intentionally benevolent or malevolent. Instead, when considering how AI might become a risk, experts think two scenarios most likely:

The AI is programmed to do something devastating: Autonomous weapons are artificial intelligence systems that are programmed to kill. In the hands of the wrong person, these weapons could easily cause mass casualties. Moreover, an AI arms race could inadvertently lead to an AI war that also results in mass casualties. To avoid being thwarted by the enemy, these weapons would be designed to be extremely difficult to simply “turn off,” so humans could plausibly lose control of such a situation. This risk is one that’s present even with narrow AI, but grows as levels of AI intelligence and autonomy increase.

The AI is programmed to do something beneficial, but it develops a destructive method for achieving its goal: This can happen whenever we fail to fully align the AI’s goals with ours, which is strikingly difficult. If you ask an obedient intelligent car to take you to the airport as fast as possible, it might get you there chased by helicopters and covered in vomit, doing not what you wanted but literally what you asked for. If a superintelligent system is tasked with a ambitious geoengineering project, it might wreak havoc with our ecosystem as a side effect, and view human attempts to stop it as a threat to be met.

As these examples illustrate, the concern about advanced AI isn’t malevolence but competence. A super-intelligent AI will be extremely good at accomplishing its goals, and if those goals aren’t aligned with ours, we have a problem. You’re probably not an evil ant-hater who steps on ants out of malice, but if you’re in charge of a hydroelectric green energy project and there’s an anthill in the region to be flooded, too bad for the ants. A key goal of AI safety research is to never place humanity in the position of those ants.

**2.6.3 WHY THE RECENT INTEREST IN AI SAFETY**

Stephen Hawking, Elon Musk, Steve Wozniak, Bill Gates, and many other big names in science and technology have recently expressed concern in the media and via open letters about the risks posed by AI, joined by many leading AI researchers. Why is the subject suddenly in the headlines?

The idea that the quest for strong AI would ultimately succeed was long thought of as science fiction, centuries or more away. However, thanks to recent breakthroughs, many AI milestones, which experts viewed as decades away merely five years ago, have now been reached, making many experts take seriously the possibility of super intelligence in our lifetime. While some experts still guess that human-level AI is centuries away, most AI researches at the 2015 Puerto Rico Conference guessed that it would happen before 2060. Since it may take decades to complete the required safety research, it is prudent to start it now. Because AI has the potential to become more intelligent than any human, we have no surefire way of predicting how it will behave. We can’t use past technological developments as much of a basis because we’ve never created anything that has the ability to, wittingly or unwittingly, outsmart us. The best example of what we could face may be our own evolution. People now control the planet, not because we’re the strongest, fastest or biggest, but because we’re the smartest. If we’re no longer the smartest, are we assured to remain in control?

FLI’s position is that our civilization will flourish as long as we win the race between the growing power of technology and the wisdom with which we manage it. In the case of AI technology, FLI’s position is that the best way to win that race is not to impede the former, but to accelerate the latter, by supporting AI safety research.

**2.6.4 THE TOP MYTHS ABOUT ADVANCED AI**

A captivating conversation is taking place about the future of artificial intelligence and what it will/should mean for humanity. There are fascinating controversies where the world’s leading experts disagree, such as: AI’s future impact on the job market; if/when human-level AI will be developed; whether this will lead to an intelligence explosion; and whether this is something we should welcome or fear. But there are also many examples of of boring pseudo-controversies caused by people misunderstanding and talking past each other. To help ourselves focus on the interesting controversies and open questions and not on the misunderstandings let’s clear up some of the most common myths.

**2.6.5 TIMELINE MYTHS**

The first myth regards the timeline: how long will it take until machines greatly supersede human-level intelligence? A common misconception is that we know the answer with great certainty. One popular myth is that we know we’ll get superhuman AI this century. In fact, history is full of technological over-hyping. Where are those fusion power plants and flying cars we were promised we’d have by now? AI has also been repeatedly over-hyped in the past, even by some of the founders of the field. For example, John McCarthy (who coined the term “artificial intelligence”), Marvin Minsky, Nathaniel Rochester and Claude Shannon wrote this overly optimistic forecast about what could be accomplished during two months with stone-age computers: “We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College […] An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.” On the other hand, a popular counter-myth is that we know we won’t get superhuman AI this century. Researchers have made a wide range of estimates for how far we are from superhuman AI, but we certainly can’t say with great confidence that the probability is zero this century, given the dismal track record of such techno-skeptic predictions. For example, Ernest Rutherford, arguably the greatest nuclear physicist of his time, said in 1933 less than 24 hours before Szilard’s invention of the nuclear chain reaction that nuclear energy was “moonshine.” And Astronomer Royal Richard Woolley called interplanetary travel “utter bilge” in 1956. The most extreme form of this myth is that superhuman AI will never arrive because it’s physically impossible. However, physicists know that a brain consists of quarks and electrons arranged to act as a powerful computer, and that there’s no law of physics preventing us from building even more intelligent quark blobs.There have been a number of surveys asking AI researchers how many years from now they think we’ll have human-level AI with at least 50% probability. All these surveys have the same conclusion: the world’s leading experts disagree, so we simply don’t know. For example, in such a poll of the AI researchers at the 2015 Puerto Rico AI conference, the average (median) answer was by year 2045, but some researchers guessed hundreds of years or more. There’s also a related myth that people who worry about AI think it’s only a few years away. In fact, most people on record worrying about superhuman AI guess it’s still at least decades away. But they argue that as long as we’re not 100% sure that it won’t happen this century, it’s smart to start safety research now to prepare for the eventuality. Many of the safety problems associated with human-level AI are so hard that they may take decades to solve. So it’s prudent to start researching them now rather than the night before some programmers drinking Red Bull decide to switch one on.

**2.6.6 CONTROVERSY MYTHS**

Another common misconception is that the only people harboring concerns about AI and advocating AI safety research are luddites who don’t know much about AI. When Stuart Russell, author of the standard AI textbook, mentioned this during his Puerto Rico talk, the audience laughed loudly. A related misconception is that supporting AI safety research is hugely controversial. In fact, to support a modest investment in AI safety research, people don’t need to be convinced that risks are high, merely non-negligible — just as a modest investment in home insurance is justified by a non-negligible probability of the home burning down. It may be that media have made the AI safety debate seem more controversial than it really is. After all, fear sells, and articles using out-of-context quotes to proclaim imminent doom can generate more clicks than nuanced and balanced ones. As a result, two people who only know about each other’s positions from media quotes are likely to think they disagree more than they really do. For example, a techno-skeptic who only read about Bill Gates’s position in a British tabloid may mistakenly think Gates believes superintelligence to be imminent. Similarly, someone in the beneficial-AI movement who knows nothing about Andrew Ng’s position except his quote about overpopulation on Mars may mistakenly think he doesn’t care about AI safety, whereas in fact, he does. The crux is simply that because Ng’s timeline estimates are longer, he naturally tends to prioritize short-term AI challenges over long-term ones.

**2.7 RELATED WORK**

IGAIN

The ‘IGain’ system is an expert system that provides an intelligent ‘Self Help’ Expert Solution for Depression patients.

The ‘IGain’ was proposed to be a web based system, accessible on computers as well as mobile devices. The system provides explicit and implicit inputs to the system to detect Depression disorder.

The ‘IGain’ system was meant to provide an intelligent ‘Self Help’ Expert Solution for Depression patients.

The proposed system has three types of users

1. Regular user (Patients or Potential Patients) – Type 1

2. Doctors / Counselors – Type 2

3. Buddies (Support Groups, People willing to help or share experience) – Type 3

Every type of user will create a user profile to store basic information. For Type 1 user, additional information which may include their hobbies, health inputs, habits, routine, preferences such as diet, doctor, entertainment, etc. will be input. These inputs will be stored in the knowledge Base and will directly be used to derive the support provided to the patient by IGain App.

For Type 2 and Type 3 users, system will input and store area of expertise, location, availability details, etc.

All users can update their IGain data, at any frequency, in any number of interactions

The system uses a Prolog Knowledge base which is initially fed with following data vetted by appropriate medical personnel:

1. Information related to Types and Levels of Depression, Symptoms of Depression, etc.

2. Conditions to identify possibility of Depression from Symptoms (Direct Symptoms, Keyword Based, etc.)

3. Base data on types and courses of treatment for various levels. This information can be used to suggest possible treatments for a patient, on case to case basis.