Efficacy of an AI-Based Weight Loss Digital Therapeutics Platform: A Multidisciplinary Perspective

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Abstract**—Obesity is a global problem that has had a significant impact on society and the economy. The consequences are ominous with serious health risks. Millions of people are dying every year from complications of obesity and comorbidities. Despite efforts by governments and health agencies obesity continues to rise. Most of the approaches to management and treat obesity have not been successful because they did not shape people's lifestyle and the solutions that were provided for lifestyle modification are not multidisciplinary, they focus on only specific aspects. Obesity management mandates multidisciplinary approach with effective patient engagement, enhanced patient-healthcare provider communication, better adherence to therapy, minimize therapeutic inertia, motivation, more informed treatment decision by the healthcare provider, and addressing psychosocial conditions. We designed and developed an AI (artificial intelligence) based digital therapeutics platform to the multidisciplinary mandate for obesity management and treatment. We tested the efficacy of our proposed platform (solution) with a 24-week field trial and achieved 13.9% weight loss of the initial weight.**

Keywords- obesity; weight loss; digital therapeutics; artificial intelligence; expert systems.

I. INTRODUCTION

Obesity has matched epidemic proportions, with at least 2.88 million people dying every year as a result of being overweight or obese and a whopping economic and social impact of $1.7 trillion dollars [1]. The costs include $1.24 trillion in lost productivity and $480.7 billion in direct healthcare costs [2]. Once associated with high-income countries, obesity is now also prevalent in low and middle-income countries. Government agencies, non-governmental organizations, and the private sectors have been publishing their expert advice as good practices for a healthy lifestyle, in their research and field trials for decades and acknowledge that this pandemic is ever-increasing.

Despite ubiquitous information about nutrition and exercise, more fitness awareness, and more food and activity tracking devices, over 42% of the US adult population is living with obesity [3]. The world obesity rate grew proportionally as well [4]. The statistics show a significant increase from a decade ago, as depicted in Figure 1. The consequences are ominous; obesity is associated with serious health risks including heart, liver, gallbladder, kidneys, joints, breathing disorders, sleep apnea, diabetes, and several types of cancer [5]. The medical community continues struggling to find successful ways to encourage weight loss and provide effective interventions.

Lifestyle intervention faces challenges like compliance issues making weight loss difficult. Despite this, it continues to be a crucial component of obesity treatment. Digital tools augment lifestyle interventions by offering personalized support catering to the need for continuous interaction and support beyond conventional primary care settings. However, there is a need for a more comprehensive approach in utilizing digital tools to address the multifaceted aspects of obesity treatment effectively.

Traditional digital health methods of lifestyle modification have limited effectiveness in managing obesity as they lack multidisciplinary approach and engagement of HealthCare Provider (HCP) . The use of AI health coaching and predictive guidance for weight loss [6][7][8][9] is comparable with in-person HCP treatment, however it lacks patient engagement and treatment adherence.

Similarly, studies incorporating remote monitoring [10], motivational, moral, and community support [11][12], accountability [13], diet and nutrition management [14][15], physical activity tracking [16], and instant communication with the coaches through text messaging and video consultation [17][18] have been tried, however with limited success as they were monomodal.

Studies combining approaches and technologies showed better results. A clinical trial conducted showed that the use of a mobile application that used AI algorithms and gamification techniques to provide personalized feedback led to a significant reduction in body weight, body mass index (BMI), and waist circumference [19]. However, there is a need for effective, holistic, adaptive, cost effective, user-friendly, and integrated digital solution to manage obesity.

In the 21st century, AI and health technological advancement have enabled the development of digital therapeutics. Digital

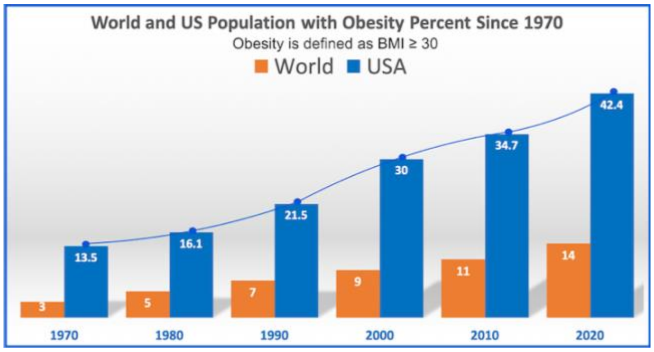

Figure 1: World and US obesity growth in the last six decades.

Therapeutics (DTx) are defined as evidence-based therapeutic interventions for patients by means of qualified software programs and medical devices to prevent, manage, or treat medical conditions.

Digital therapeutics can be more flexible than other treatment methods to address patients' individual needs [20]. These technologies employ various techniques, such as mobile applications, wearable devices, and online platforms, to improve the effectiveness of treatment interventions [21]. However, the current metabolic conditions such as obesity, diabetes, and cardiovascular diseases AI-based DTx would be an ideal complement to the pharmaceutical or even surgical weight loss offerings.

AI along with related technologies offer a promising approach for the management of obesity, as they use Machine Learning (ML) algorithms and/or expert systems (ES) to personalize treatment plans for patients.

We propose an AI-based DTx integrating all the approaches tried before but individually in a unified single platform, SureMediks. It includes short-term goals approach, tailored AI-based guidance and education on diet, nutrition, physical activities, and psychosocial conditions, effective and interactive patient-HCP communication, remote monitoring, motivation, accountability and community support.

SureMediks (our platform) includes an ES. Expert system is a branch of artificial intelligence (AI) that mimics the decision-making processes of human experts in specific domains. These systems are designed to provide guidance, advice, and recommendations to users based on their input and the knowledge (KB) rules programmed into the system [22]. These rules in KB can be updated as system learns new facts about the patients and their behavior. The integral components of an ES and its operation are depicted in Figure 3. The Knowledge Acquisition System of the ES extracts the expert knowledge and saves (learns) it in Knowledge Base (KB) as rules. Inference Engine (IE) activates these rules based on current and historical data and provides the guidance and education stored and learned in the KB. IE also updates the rules in KB dynamically. Explanatory Systems interprets patient's data and explain to the patients through charts and graphs in the mobile app.

In the context of patients' guidance and education, expert systems can provide personalized and interactive programs for managing and treating various health conditions, including obesity [23] and diabetes [24][25]. These systems can analyze patient data, such as medical history, symptoms, and lifestyle factors, and provide tailored recommendations and interventions to support patients in making informed decisions about their health.

AI feedback system was designed to address the primary barriers to successful weight loss, such as the complexity of dietary information, ineffective motivational strategies, and intermittent physical activity. By delivering real-time personalized feedback, SureMediks helps individuals remain on track, and offer corrective strategies when necessary. Additionally, it offers access to human expert guidance, which can further help individuals develop healthier behaviors that last longer.

The weight loss participants who reach their short-term goals have better long-term weight loss and ambitious short-term goals in the future[26] [27]. We used Khokhar WL Formula [28] to generate short-term goals, the formula is depicted in the equation below:

$$W_{loss} = \frac{\Delta W}{1-e^{-\frac{r\tau}{10}}}\left(e^{-\frac{rn}{10}} - e^{-\frac{r\tau}{10}}\right);\ r,\tau \neq 0; \quad \text{(Equation 1)}$$

Here, W_{loss}, ΔW, τ,and r are weight to lose at each short-term goal, total weight loss, time to lose weight in weeks, and r is a special parameter respectively, we called, r, the curve tension, n is the week number. For example, for n =1, 2, 3, it will determine the required weight loss for the first, second, and third weeks.

To assess the efficacy of our proposed AI-based DTx platform, SureMediks, we developed a prototype of the platform and set it up for a field trial. The implemented features and expert system's knowledge base were derived from a large research body and field trials mentioned previously in this section. In this paper we report summary of the filed trial and the results.

II. METHOD

This section describes our AI-based platform, SureMediks, field validation covering participants details, procedures and measurements.

A. Platform

Our platform consists of the following key elements: 1) An Internet-connected body composition scale to get patient's weight and related body metrics, 2) A mobile application through which patients receive tailored guidance, education, motivation, communicate with the HCP, interactive with accountability circle members for community support and visually can see the weight loss progress, 3) An AI agent acting as an expert system, and 4) A dashboard for the HCP to view patients' weight loss progress and interact with the patients.

B. Participants and weight loss goals

A participant sample of 1137 people of age 21 years and older from the USA, Canada, UK, and Australia were invited through emails and a weblink to participate in this field study. They were provided with key screening questions if they were determined and committed to losing weight that year, ready to be strictly focused on weight loss, ready and committed to be on a low-calorie trackable diet with daily trackable physical activity.

Finally, 391 participants took part in the trial from start to end. Of the 391 participants, 59% of the participants were female and 41% were male. Their education level, marital status, and other socioeconomic factors were not part of our selection criterion. However, their current weight, BMI, and age were among the primary concerns as we wanted to have diversity in age and weight buckets. Their start (baseline) mean weight, $\boldsymbol{\mu_{Start}}$, was 124.6 Kg with a standard deviation, $\boldsymbol{\sigma_{Start}}$, of 31.57 Kg, and a wide range of 65-181 Kg weight distribution. Mean age of the participants, $\boldsymbol{\mu_{Age}}$, was 43.56 years with a standard deviation, $\boldsymbol{\sigma_{Age}}$, of 12.60 years, and the range of 21-71 years. Their BMI mean, $\boldsymbol{\mu_{BMI}}$, was 43.9 Kg/m^2 with SD, $\boldsymbol{\sigma_{BMI}}$, of 8.5 Kg/m^2, $30 > BMI > 25$ was considered overweight and $BMI \geq 30$ was considered obesity as per World Health Organization (WHO) generic guidelines. The weight loss goal was 10% of the start weight however we set a stretch goal of 15% as the majority of the participants insisted on raising the bar.

C. Procedure and measures

The participants were provided with a WiFi-enabled smart body composition weighing scale and a mobile app, SureMediks. The study coordinators and coaches collaborated with the participants through a dashboard. The coaches, who were nutritionists, dietitians, and exercise instructors, had their own dashboards which they could log in and manage, communicate, and monitor the participants' progress, food intake, and physical activity. Figure 2 shows the high-level architecture of our implementation.

We created six groups of 391 participants based on their weight in six different weight buckets. Bucket 1 with participants of 65-85kg of weight, Bucket 2 for 86-105kg weight, Bucket 3 for 106-125kg, Bucket 4 for 126-145kg, Bucket 5 for 146-165kg, and Bucket 6 for the participants with the weight of 166-181kg. Our weighing scale maximum capacity was 181 Kg. These six weight buckets had 61, 78, 83, 60, 66, and 43 participants respectively, totaling 391 participants.

The participants in the study downloaded and installed the app on their smart devices and register their smart scale by scanning its ID or entering it manually. They provide their information, including age, height, preferred units, physical activity level, desired weight loss, duration, and group number. After signup, they were added to their coaches' dashboards. The baseline metrics were established automatically when they stepped on the scale for the first time, and weekly goals were sent by the intelligent agent based on the Khokhar WL formula [28]. The curve tension, r, adjusts dynamically based on weight loss performance, and participants are moved to a more suitable curve if they struggle to reach their weight loss goals.

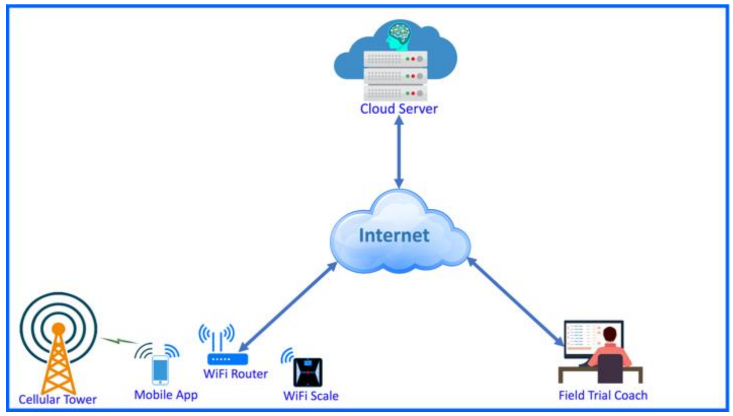

Figure 2: High-level implementation of the architecture: the participants have the scale and app, whereas the coaches have dashboards.

In this study, participants received feedback from an intelligent agent (ES) based on their current and historical data, each time they stepped on the scale along with education and guidance through the ES. The flow of ES is depicted in Figure 3. Two sample feedbacks are shown in Figure 4. Coaches also interacted with participants through text messages and video calls. The participants followed a low-calorie diet recommended by AI-based feedback mechanisms and the coaches, with food items shown in the app. Physical activity was chosen from a menu and tracked by AI and coaches. Participants were encouraged to step on the scale at least twice a week and could track their progress through charts in the app. Coaches focused on metabolic rates and weekly weight loss, providing additional guidelines if goals were not achieved. Participants formed accountability circles for support and motivation, and alerts were set up to notify if weight gain occurred. Participants were proactive in making corrections to their diet, physical activities, and lifestyle based on feedback and guidance from the ES.

SureMediks, encouraged participants to engage in challenges within their accountability circle, facilitated by the app. There were six challenges to lose 3% weight each, and the platform tracked the number of challenges participants took part in. In addition to community support, participants received daily motivational quotes selected by the AI agent based on their progress or challenges. After 26 weeks, participants' weekly weights were noted and their weight loss progress statistics were analyzed using MS Excel data analysis tools.

D. Results

The detailed weight loss statistics of each of the six buckets is as follows: For Weight Bucket1, 65-85 Kg, the

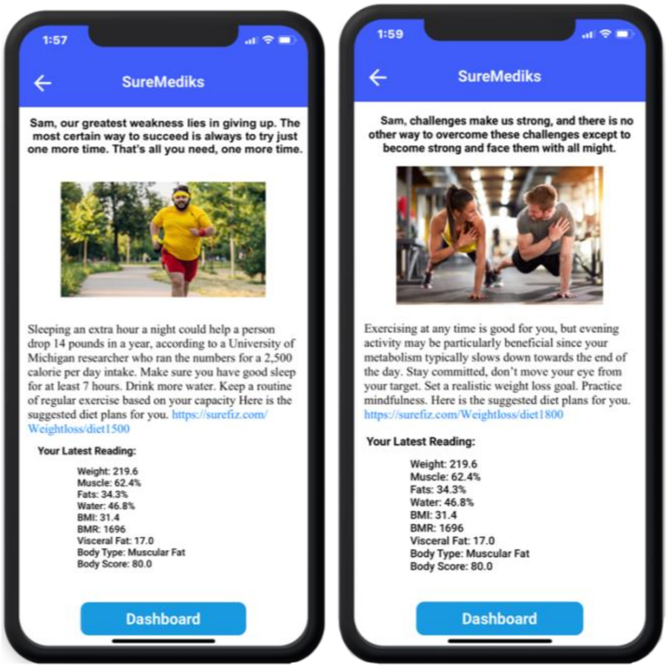

Figure 4: Samples of guidance from the ES, first part is motivational and second part is feedback and guidance.

mean weight loss, μ_{wl1}, was 10.1 kg, standard deviation, σ_{wl1} = 3.4 kg, mean weight loss percentage of 13.3, with a 95% confidence interval (CI) of 12.18% -14.38%, and BMI loss (drop) of 4.3 points. For Weight Bucket2, 86-105 Kg, the mean weight loss, μ_{wl2}, was 13.6 Kg, standard deviation, σ_{wl2} = 4.4 Kg, mean weight loss percentage of 14.2, with a 95% confidence interval (CI), 13.20% -15.19 %, and BMI loss (drop) of 5.2 points. For Weight Bucket3, 106-125 Kg, the mean weight loss, μ_{wl3}, was 15.9 Kg, standard deviation, σ_{wl3} = 5.2 Kg, mean weight loss percentage of 14.0, with a 95% confidence interval (CI), 13.03% - 14.96%, and BMI loss (drop) of 5.9 points. For Weight Bucket4, 126-145 Kg, the mean weight loss, μ_{wl4}, was 19.1 Kg, standard deviation, σ_{wl4} = 5.9 Kg, mean weight loss percentage of 14.5, with a 95% confidence interval (CI), 13.41% - 15.58%, and BMI loss (drop) of 6.8 points. For Weight Bucket5, 146-165 Kg, the mean weight loss, μ_{wl5}, was 19.4 Kg, standard deviation, σ_{wl5} = 6.8 K, mean weight loss percentage of 12.53, with a 95% confidence interval (CI), 11.45% - 13.60%, and BMI loss (drop) of 6.7 points. For Weight Bucket6, 166-181 Kg, the mean weight loss, μ_{wl6}, was 25.5 Kg, standard deviation, σ_{wl6} = 7.3 Kg, mean weight loss percentage of 14.8, with a 95% confidence interval (CI), 13.54% - 16.07% , and BMI loss (drop) of 8.6 points.

Overall, for all 391 participants, 65-181kg, the mean weight loss, μ_{wl}, 17.27 Kg, with standard deviation, σ_{wl6} = 7.0 Kg, mean weight loss percentage of 13.89, with a 95% confidence interval (CI), 13.45% – 14.35%, and BMI loss (drop) of 8.6 points. The p-value was significant, $p < 0.0001$, for all results, confidence interval (CI), 13.54% - 16.07% ,

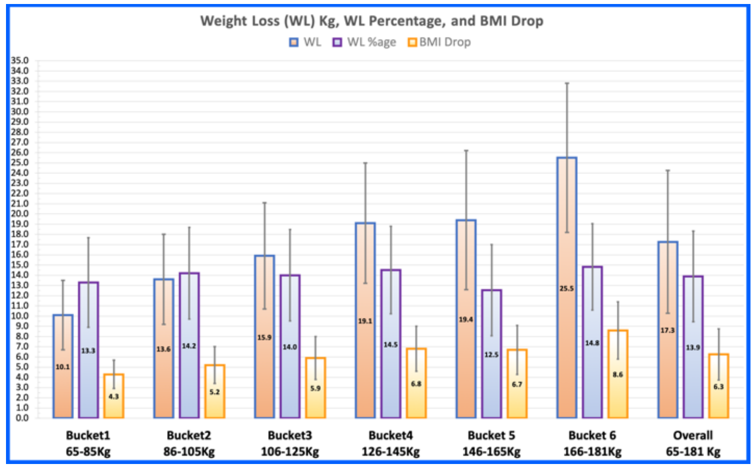

Figure 5: Higher BMI drop with larger weight buckets. the weight loss percentage is similar across all the buckets.

and BMI loss (drop) of 8.6 points. Figure 5 depicts the key results: mean and standard deviation of weight loss, weight loss percentage, and BMI loss (drop).

Figures 6 shows the weekly plotted mean weight loss progress in kilo grams of all the buckets combined (391 participants). In this plot, the Amber curve depicts the weekly weight loss progress for the period of the trial and the blue line shows the weekly predicted mean weight of the participant per the Khokhar Weight Loss formula (Equation 1). The predicted weight loss curve could serve as the trend curve as well.

III. Discussion

This study suggests that digital platforms are efficient for weight loss programs. We found that participants had a mean weight loss of 13.9% from baseline using an AI-assisted lifestyle intervention only. The study set a stretch weight loss goal of 15% based on participants' preferences and determination which was found to play a vital role in weight loss efforts. Dividing the weight loss goal into smaller weekly goals made it less overwhelming and increased participants' sense of control and confidence. The study also found that AI guidance, extensive communication and guidance from coaches, motivation, accountability, and community support were driving factors in achieving these outstanding weight loss goals. The use of timely guidance and feedback, along with extensive communication, led to better outcomes. Motivation derived from internal and external factors, along with accountability and community support, played significant roles in participants' weight loss. Food journaling and physical activity tracking also contributed to healthier food choices and increased physical activity. Overall, a comprehensive approach with the optimal use of technology is effective for weight and obesity management.

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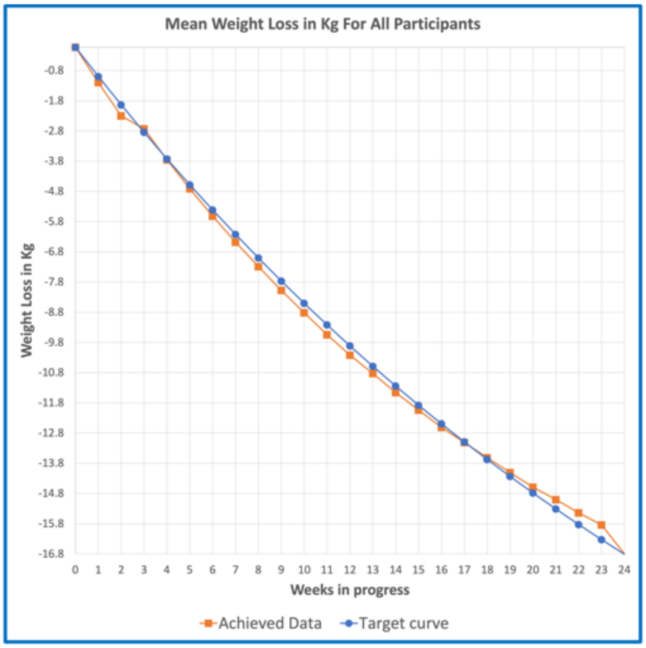

Figure 6: Weekly weight loss progress of all 391 participants. Average weekly weight loss was 0.71 Kg.

IV. CONCLUSION AND FUTURE WORK

Consistent weight loss needs a multidisciplinary approach. Determination, motivation, effective communication, diet, physical activity, accountability, and tailored guidance and education are vital elements. Digital therapeutics for obesity have the potential to significantly improve patient adherence and treatment outcomes and can deliver a framework where these key elements asynchronously and coherently work for the best patient-HCP engagement and optimal patient outcome. It is a promising way to address the global pandemic of obesity and warrants significant investment for further development. AI plays a vital role in delivering tailored guidance and education to the patient and catalyze the effectiveness of DTx. With a properly designed and operated digital therapeutics platform surpassing the benchmark of 10% weight loss in 24 weeks is feasible with an effective diet and physical plan along with the vital elements of a multidisciplinary approach, which a DTx platform can deliver effectively using ES.

Our future work is focused on studying how SureMediks can effectively complement medical weight loss with Glucagon-Like Peptide (GLP-1) and similar weight loss medication and post metabolic surgery weight loss.

ACKNOWLEDGMENT

We would like to thank our participants and their commitment to their dedicated time. Their compliance and dedications to our field trial were commendable. We would also like to thank Mr. Kannan Palaniswami for his efficient technical support and Ms. Helga Andersen for her moral support for completing the field trial and compilation of this paper.

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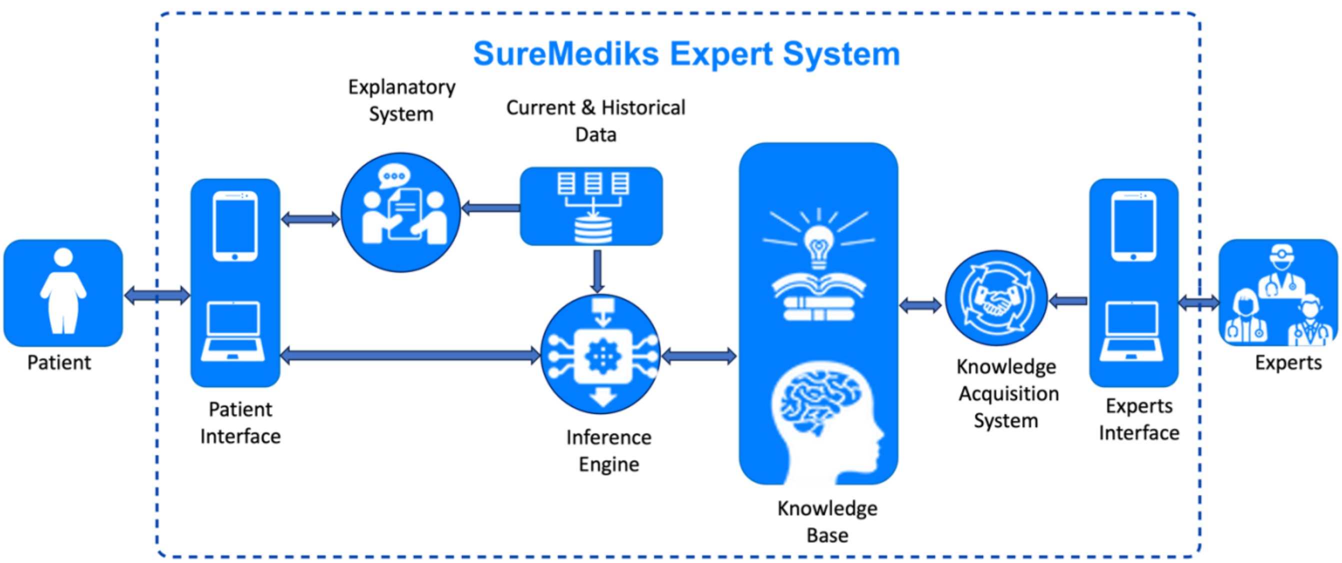

Figure3: Distributed Architecture and the operation flow of our SureMediks Expert System.