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Personal Wellness: Complex and Elusive Product and Distributed Self-Services

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Abstract

In many countries across the world a universal issue of growing concern is increasing demand for health services and corresponding escalating costs. While there are many reasons for these two trends, reasonable solutions are nowhere in sight and a subject of heated debates. One potential source of relief for the health care systems is to shift some (if not majority – but in long term) of responsibilities to patients themselves. To do so effectively, however, better definition of personal well-being is needed, supported by medical knowledge transfer to the consumer and creation of some personal health management tools. Service engineering concepts, such as service package, are useful in decoupling all elements needed to develop an infrastructure in support of wellness as a core product and addressed by variety of limited-focus services.

This paper reviews the emerging health care paradigms, in particular health care networks, consumer-personalized medicine and quantified self-tracking. With the Quantified Self movement on the rise for the past several years and a corresponding growth in offering of tools for variety of personal data collection (both hardware- and software-based), the obvious question arises how effective they are and what impact they actually have. The discussion also addresses the question whether it is possible to reframe the personal health issues by applying both design thinking and service engineering approaches aimed at individual's own well-being.

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1. Introduction

There is overwhelming rise in demand for improved healthcare services and facilities globally especially in developed nations in recent years [1]. It imposes enormous pressure on current government and insurance policies regarding healthcare in coping up with this surge in financial terms. Along with hike in cost other challenges like decentralized, uncoordinated competencies, low competition intensity, monolithic structures with low division of labor and inadequate quality management are plaguing this sector [2]. The present health care structure has in-built cost centers, which should be restructured by incorporating service engineering concepts and design thinking to reduce the avoidable burden. Thus there is need for paradigm shift in outlook towards envisaging healthcare as a service where patients collaborate with healthcare professionals in laying the foundation stone of healthy society. It can materialize by utilizing technological advancement and making patients knowledgeable enough to share their part of healthcare responsibilities [3].

By integrating divergent disciplines like pharmacy, biotechnology, nanotechnology, IT, electronics, and service engineering; new tools and models can be developed which will enable healthcare services to be customized and packaged as per demand. Penetration of internet into every personal gadget provides opportunities to monitor and track biometric parameters which can be used to determine the health index at individual, regional or national level. Personalized, participatory, predictive and preventive approaches to tackle diseases can be formulated by analyzing human genome at personal level [4]. Online interaction among patients and physicians via healthcare networks can help in knowledge sharing and decision making regarding treatment beyond space and time constraints. These emerging trends can act as a

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beacon for directing future research, government and insurance regulations and policies [5].

Different patient and technology driven healthcare models can be developed, based on enormous self-collected digital information and stored online by the patients and ongoing researches. The effectiveness and efficiency of these models can be verified by estimating the reduction in cost and increase in awareness and health of patients. But its implementation will have to overcome challenges related to privacy, security, regulations and capability to cope up with new emerging issues [6]. In this paper, main focus will be on the effectiveness of these models in restructuring the personal healthcare services by incorporating service engineering concepts for smooth transition of personal wellbeing responsibility on patients. Obesity is emerging as most prominent health issue responsible for over 60% deaths in developed nations. Obesity Predictive Model is personal health management tool which needs self-collected data to predict personal well-being status [1].

2. Paradigm shift in health care sector towards self-service

In 2013, U.S. expenditure on healthcare surpassed $ 2.8 trillion; raised serious issues demanding transformation in current health care structure [7]. Several social, structural and behavioral reforms focused on shifting some of the responsibilities towards consumer have already begun. Health Care Kiosks installed at hospitals assist patients in self-check-in, information retrieval, scheduling appointments, way finding, self-checkout at reduced waiting time, lower paper and labor costs, less information entering errors with enhanced patient satisfaction and accuracy [7]. According to survey conducted by Accenture [8], “90% patients want to self-manage their healthcare leveraging technologies such as accessing medical information, refilling prescriptions and booking appointments online”.

Service engineering concepts and design thinking can be applied for health care restructuring targeted at patient’s wellness. Individual units and operations should be detected and decoupled based on their potential to enhance self-service. As health care sector is a complex system, its holistic behavior cannot be determined by having knowledge of individual components’ behavior located at various levels. These components are heterogeneous, mutually dependent and inter-related non-linearly with feedback loops across different levels [9].

Self-service oriented healthcare restructuring requires multilevel, adaptive, continuously evolving and dynamically changing modeling of complex system. Decision making should be decentralized at multi-levels i.e. at individual, physician, institutional, government and insurance policy makers’ level [10,11]. As conventional, centralized, top-down approaches doesn’t work in complex decision making. Agent based Computational Modeling, System Dynamics Approach, Dynamic Micro-Simulation and Markov Model are the prominent modeling techniques being implemented in this sector [9]. System Dynamic Approach for modeling complex obesity problem has been most widely implemented targeting self-monitoring and tracking [1].

3. New patient-driven and technology-enabled models

Advancement of technology and increasing health related awareness of patients are boosting the development of new personal wellness models. Implementation of these models requires self-gathered data using personal gadgets and know-how to interpret the results [3]. The three main currently emerging approaches are discussed below:

- Health Social Networks
- Consumer Personalized Medicine
- Quantified Self-tracking

3.1 Health social networks

Social networks have emerged more than just platform for sharing personal beliefs and ideas into more structured knowledge sharing, research and business clusters which have the potential of recognizing trends and patterns and guide decision making. In healthcare sector various networking platforms like PatientsLikeMe, CureTogather, DailyStrength, MedHelp, HealthChapter, MDJunction and OrgannizedWisdom have emerged recently which provide services at four different levels i.e. emotional support and information sharing, physician question and answer, quantified self-tracking and clinical trial access [3]. Patients interact with other patients with similar conditions as well as with physicians and exchange knowledge to become more aware of their situation. They upload their biometric data collected through self-monitoring on various available tools on these websites to evaluate their health status and consult appropriate remedy as well. This online counseling eradicates space and time barriers [5]. It also transcends translational medicine by bridging patients and researchers and enabling real time feed-back for analyzing research needed and research conducted. It provides a common platform for interaction among patients, physicians, employers, regulators, policy-makers and insurance agencies to gain insight into health status and confronting challenges from individual level to community as a whole [12, 3].

3.2 Personalized medicine

Personalized medicine is an emerging multi-disciplinary therapeutic approach based on personal and genetic variation whose market is estimated to grow up to $452 billion by 2015 [13]. This dream is becoming a reality due to development of high throughput genetic technologies that enabled human gene sequencing, detection and manipulation possible at affordable price [14,15,16]. With the completion of Personal Genome Project, new arena of genetic based predictive and preventive targeted drug formulation therapies have opened up [17,15]. Direct-to-consumer physician mediated genetic

biomarker testing services are empowering patients to track their health status on regular basis [15]. Standard health risk assessment can be performed by incorporating biomarker profile data into mathematical models to predict individual's likelihood of chronic diseases [3]. Bio-simulations provide opportunities to develop safer and cost effective drugs also to determine their dosage, efficacy and toxic effects [14,3]. Consumer directed health care services requires online storage of personal genomic and health information on public or institutionalized portals. It can be analyzed to stratify patients with similar disorders and can be utilized for performing targeted clinical trials [4].

3.3 Quantified self-tracking

The current surge in healthcare awareness led to emergence of next generation of self-conscious individuals known as "Qsers", who are constantly engaged in quantifying their self by using smart gadgets [6]. By 2020, 24 billion internet connected devices are estimated to surpass $ 4.5 trillion [18]. Latest devices like smart watches, wrist band sensors, monitoring patches, smart phones, brain-computer interface, neuro sensing, emotional mapping, home automation sensors and environment monitoring sensors have enabled gathering and monitoring of personal, home and environmental data like weight, heart rate, blood pressure, body temperature, ECG, EEG, etc [18]. Data collected by biosensors can be uploaded on Personal Health Records on continuous basis by wireless connectivity to track, know, evaluate and manage performance. Personalized data can be integrated into social management systems to detect anomalies, correlations, patterns and recognize core drivers of human behavior at individual or global level. Crowdsourcing can be performed by using GPS and GIS to spot spread of epidemic [19]. Qualitative parameters like mood, behavior and emotions can also be tracked by monitoring quantitative parameters [18,20].

4. Obesity model based on System Dynamics approach

Obesity epidemic has emerged as a major health challenge in developed nations given the impact the "age of abundance" had on change in population lifestyles and health. It is a very complex, intertwined set of relationships, where contributing factors like, for example, genes, neurobiology, psychology, family structure and influences, social context and behavioral norms, environment, markets and public policies are spread and interact across various levels. Mechanisms, linkages and feedback between them are not clearly understood, but some selected mechanisms operating at a particular level have been identified and motivated development of complex models [9].

The body weight model used in the presented work is based on the principle of energy balance (see Fig. 1). The key element associated with the energy intake is Food (both solid and liquid) consumption. On the other side, the main two elements associated with energy expenditure are Physical Activity factor (PAF) and Basal Metabolic Rate (BMR).

The core causal relationship is the Harris-Benedict equation (originally published in 1918, and refined through recent research) for calculating the Basal Metabolic Rate, or BMR (in kcal/day) as the main driver. Age, Gender, Weight and Height are the inputs to this function. Two forms of the equation, for males (M) and females (F) are widely used [21,23]:

$$BMR_M = 13.75Weight + 5Height - 6.76Age + 66 \quad (1)$$

$$BMR_F = 9.56Weight + 1.85Height - 4.68Age + 65.5 \quad (2)$$

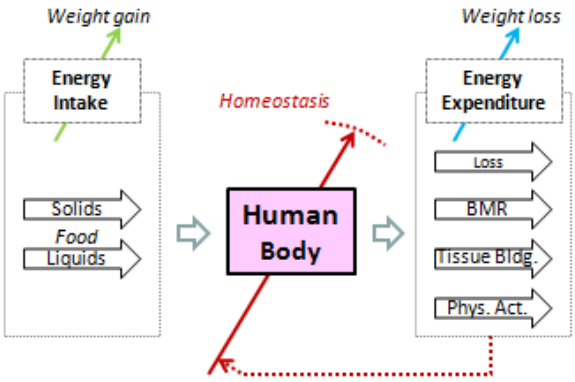

Fig. 1. Human body energy balance scheme

BMR is then becoming an input to two parallel relationships, one referred to as the Butte's transfer function [21], which captures three components affecting the energy balance, namely BMR, Energy Intake (EI), and Physical Acivity Factor (PAF) to predict the total energy cost of weight gain, and obligatory increase in the energy intake and/or decrease in physical activity level, associated with weight gain (e.g., change in body mass):

$$\frac{dBM}{dt} = f(PAF, BMR, EI) \quad (3)$$

The other physiological relationship is informed by the relatively recent research in the field, indicating that the energy consumed is also partially transformed into either fat or lean tissue [22]. While not as impactful as the other two elements, it can account to up to 20% of the overall contribution. The remaining element is any potential loss of energy occurring through the usual idle body operation.

To build a comprehensive model reflecting the time-varying nature of body weight changes and fluctuations, a System Dynamics methodology was used. System dynamics is an approach to understanding the behavior of complex systems over time. The focus of SD is on the interaction between physical processes and information flows to create the dynamics of the variables of interest. The structure of the system is defined by the totality of the relationships between these variables. Therefore, the structure of the system operating over time produces its dynamic behavior patterns.

The structure of SD models contains flow (rate) variables, stock (level) variables, and auxiliary variables. Flow variables are the components that determine the variation of stocks (entities entering and leaving the system, e.g. a body). Stock variables are the accumulations within the system (e.g., body mass gains).

The basic SD objective is to understand the structural causes that trigger system performance, and to that end, system is represented as a causal loop diagram. It includes the key factors of the system and the relationships among them based on the causes which have influence on the effects. Causal loop diagrams serve two main purposes. First, they can be applied as preliminary sketches of causal hypothesis during model development and second, they can make a simpler representation of a model. A causal loop diagram describes the major feedback mechanisms which are either negative feedback or positive feedback. Negative loops have a stabilizing effect, while positive ones may lead to instability. The systems usually contain both loop types and the final performance depends on which one is dominant.

The human body is a complex homeostatic mechanism, managing a multitude of highly complex interactions to maintain balance or return itself to functioning within a normal range. These interactions within the body facilitate compensatory changes supportive of physical and psychological functioning. Body weight management relies on the same principles of homeostasis, however abundance of food leads often to homeostatic imbalance and weight gain. SD approach enables to map the links between weight gain stimuli, physiological relationships discussed previously, and control mechanisms by use of the causal loops.

All of the above considerations were used to develop Complex Obesity Model as shown in figure 2, by using System Dynamics Approach for understanding temporal obesity behavior [1]. VENSIM software was employed for quantitative analysis of complex system by incorporating feedback loops, stocks and flows and delays. Design thinking approach was followed as inputs emerged from those parameters which were identified by system dynamics as crucial to customers [24].

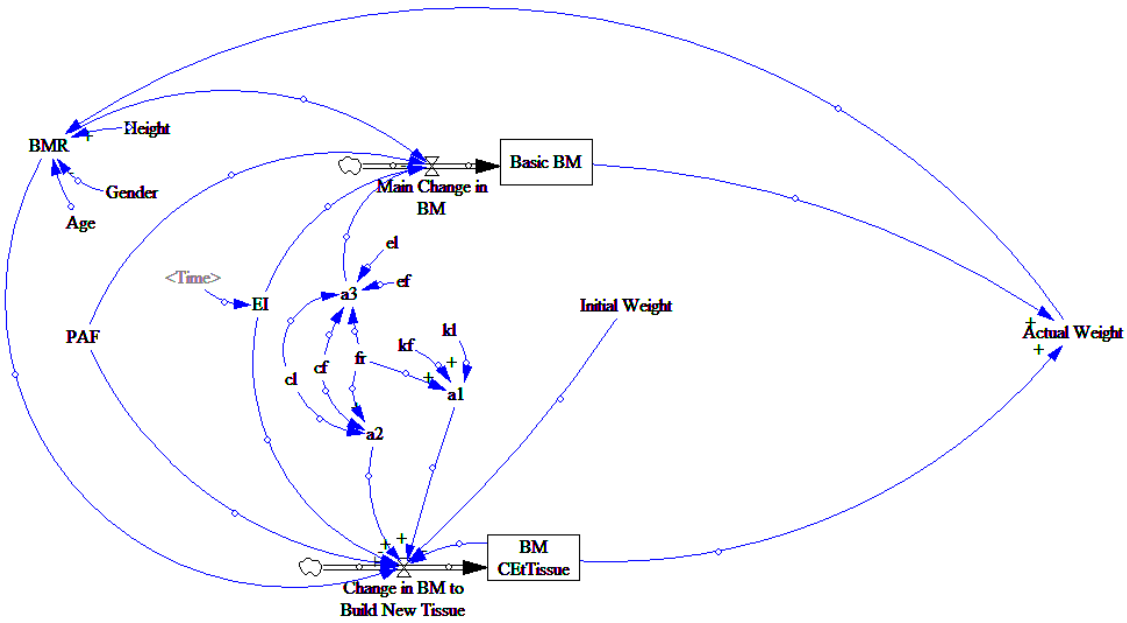

Fig. 2. Obesity model based on System Dynamics (SD) approach

The remaining coefficients appearing in the model are as follows (in parentheses are the values used in simulation runs):

fr - Fraction of fat in the new tissue (fr_{male} = 0.67 and fr_{male} = 0.76)

cf, *cl* - Energy stored per kg fat and lean tissue, respectively [MJ/kg] (*cf* = 38.9; *cl* = 4.84)

kf, *kl* - BMR per kg fat and lean tissue, respectively [MJ(kg*day)] (*kf* = 0.027; *kl* = 0.116)

ef - efficiency of energy conversion into new fat tissue (*ef* = 0.85)

el - efficiency of energy conversion into new lean tissue ($el = 0.55$)

The coefficients *a1*, *a2*, *a3* are aggregates of multiple previously defined coefficients [20]

$$a1 = (kf)(fr) + (kl)(1 - fr) \quad [\frac{MJ}{kg \cdot day}]$$

$$a2 = (cf)(fr) + (cl)(1 - fr) \quad [\frac{MJ}{kg}]$$

$$a3 = \frac{(cf)(fr)}{ef} + \frac{(cl)(1 - fr)}{el} \quad [\frac{MJ}{kg}]$$

The value of PAF was set at 1.375 (corresponding to the sedentary level of activities) or 1.7 (moderately active).

The simulated results were compared with field data obtained from a weight loss clinic (sample size of 28 individuals). The model was able to make relatively accurate predictions in real time, but many external factors (e.g., physical environment, education levels, stress, etc.) were not considered, thus results should be interpreted with caution.

Graphs in Figs. 3 and 4 show examples of weight tracking for individual patients (male and female) over a period of 19 weeks. The patients were following a regimen of a very strict diet of 500 calories per day. Weight tracking accuracy of the model falls broadly within ±8% band.

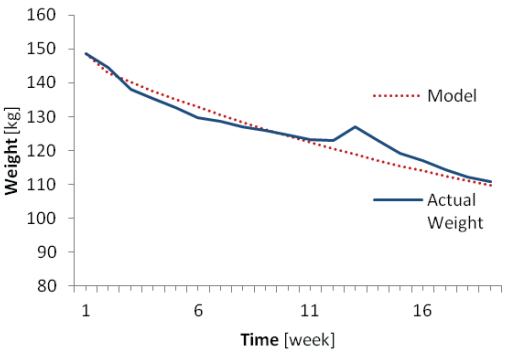

Fig. 3. Simulated vs. actual weight tracking for a 39-year old male

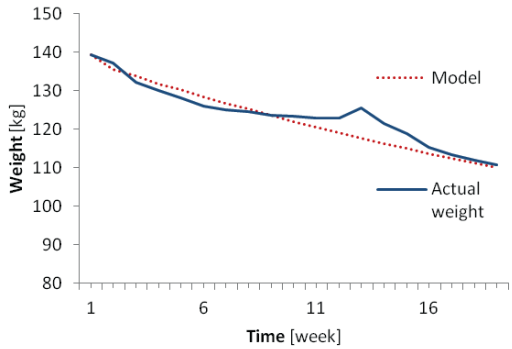

Fig. 4. Simulated vs. actual weight tracking for a 39-year old female

5. Challenges and future scope

The emerging trends in the healthcare are redefining its structure in entirely unique way and its impact and direction being unclear [18]. There are many hurdles lying along its path. Security of enormous private data will be at stake [19]. Appropriate rules and regulations should be framed for infusing enough confidence in stakeholders to encourage them to share their personal and genomic data [16]. Moreover the current technology is expensive, manual, uncomfortable and onerous involving a deal of consumer personal attention and involvement [18]. Other major challenge arising out of cultural, philosophical and sociological aspects is prevailing mind-set of masses that wellness is responsibility of physicians and healthcare related information is deterministic, negative and unwanted. Attaching financial incentives with health can help in overcoming this challenge [6].

With development of microprocessor chip miniaturization, enhanced battery life, automation, ubiquitous wireless network availability, modular nano-electronics available at low price and increased efficiency will promote wide acceptability of self-tracking [18]. Wearable electronics having mobile phone connectivity by RFID or NFC and cloud based big data services will enable continuous personal information collection on personal information management system, real time problem solving and optimization at individual or community level [7,24]. Self-tracking targeting technology led to development of complex multi-level healthcare models focusing every node of wellness cycle especially the beginning phase promoting prevention than cure [3]. Quantified-self data can be co-related with qualified-self parameters like mood, emotions, happiness and productivity to create qualified feedback loops for enhancing quality of life in terms of happiness, well-being, goal achievement and stress reduction. This quantified-self movement is envisioned as precursor of much more broadly reaching exoself movement [6].

6. Conclusion

Healthcare sector is undergoing a complete paradigm shift with evolving complex multilevel modeling; patients sharing more personal health responsibility; physicians becoming counselors; continuously evolving, interacting, and influencing social networks; changing economic, legal and regulatory structure; horizontally and vertically stratified clinical trials and personalized drug discovery and delivery [9,10,3,18,20]. Various self-assessment tools are present but not available in packaged form for specific consumers. On-going restructuring is advancing self-service and enabling bundling of services to be delivered as healthcare packages. The boom in personal data collection tools has made a significant impact in healthcare sector [3]. Developed models are able to predict the outcomes with high accuracy. Healthcare social networks have become a significant platform for patients' and physicians' interaction and knowledge sharing [12]. There is high demand for self-tracking and monitoring gadgets [18]. These tools have made a notable influence in healthcare sector but their effectiveness as preventive, guiding and regulatory agents will become clearer with further progress in restructuring in near future.

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