Towards Health Care Service Ecosystem Management for the Elderly

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Abstract

As an increasing percentage of the global population joining the elderly age group, more financial strain is being placed on health care institutions and governments worldwide. To alleviate this problem, it is necessary to involve volunteers with various skills and backgrounds to help serve part of the elderly's health care needs. Future health care service digital ecosystems have been envisioned to serve this purpose. However, there is a lack of management mechanisms for them that can holistically balance the goals of various stakeholders. In this paper, we provide a vision to face the challenge of health care service ecosystem from an interdisciplinary perspective. We propose a novel computational approach to simplify the problem of health care service ecosystem management and model it as a constraint optimization problem. By focusing on the stability and efficiency in usage health care information resources, the formulation articulates actionable objectives and constraints to make scalable and real-time solutions possible. Under such a vision, we discuss potential future research directions in the area of utility function formulation, game theoretic analysis and accommodating the special preferences of the elderly.

Keyword: Health Care, Service Orientation, Digital Ecosystem Management.

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I. Introduction

Background

The world is facing an unprecedented wave of global population aging. The most serious situation is occurring in Japan, where the percentage of people aged 65 or older has risen from 12.0% in 1990 to 23.3% in 2011, and is projected to reach 38.8% in 2050 [1]. In Singapore, elderly people consist of 11.1% of the entire population in 2012 [2]. The figure was only 7.7% in 2001. In 2050, 22% of the entire global population is projected to be aged 60 or older [3].

As people age, they tend to become susceptible to various cognitive and physical deteriorations such as dementia, impaired hearing and vision, etc. Statistics have shown that more than two thirds of hospitalized stroke patients are aged 65 or above, and the risk of stroke increases with age [4]. Once people reach 60 years of age or above, the risk of Parkinson's Disease increases drastically [5]. In [6], it has been found that as many as 49.9% of elderly people in the U.S. suffer from at least one geriatric condition, which in turn leads to dependency on other people for simple daily activities.
A rapidly ageing population will put heavy pressure on health care facilities and public finances [7]. This is especially the case for welfare states such as the U.S. and most European nations. Compounded by the implications of the global finance crisis, it is highly challenging to significantly increase public spending on health care for the elderly [8]. The future elderly health care landscape will inevitably rely more on providing low cost alternatives to allow the elderly and their loved ones to engage in self-help when looking for health care related information.

To reduce the financial costs for health care service provisioning, the key approach is to set up online communities of interest backed up by information and communication technology (ICT) to allow an online crowd with diverse background and knowledge to satisfy the elderly's health care needs. The health care needs here refer mostly to their health care information needs (e.g., gaining more knowledge about a particular type of condition, finding self-help groups for a particular type of disease, consulting health care professionals for advice on diets). An example of such an initiative is the Healthbook online social networking environment [9]. The technological platform and the various stakeholders making up such communities of interest form the basis of a future health care service ecosystem. The main characteristic of such an ecosystem is its heavy reliance on voluntarism.

The Health Care Service Ecosystem

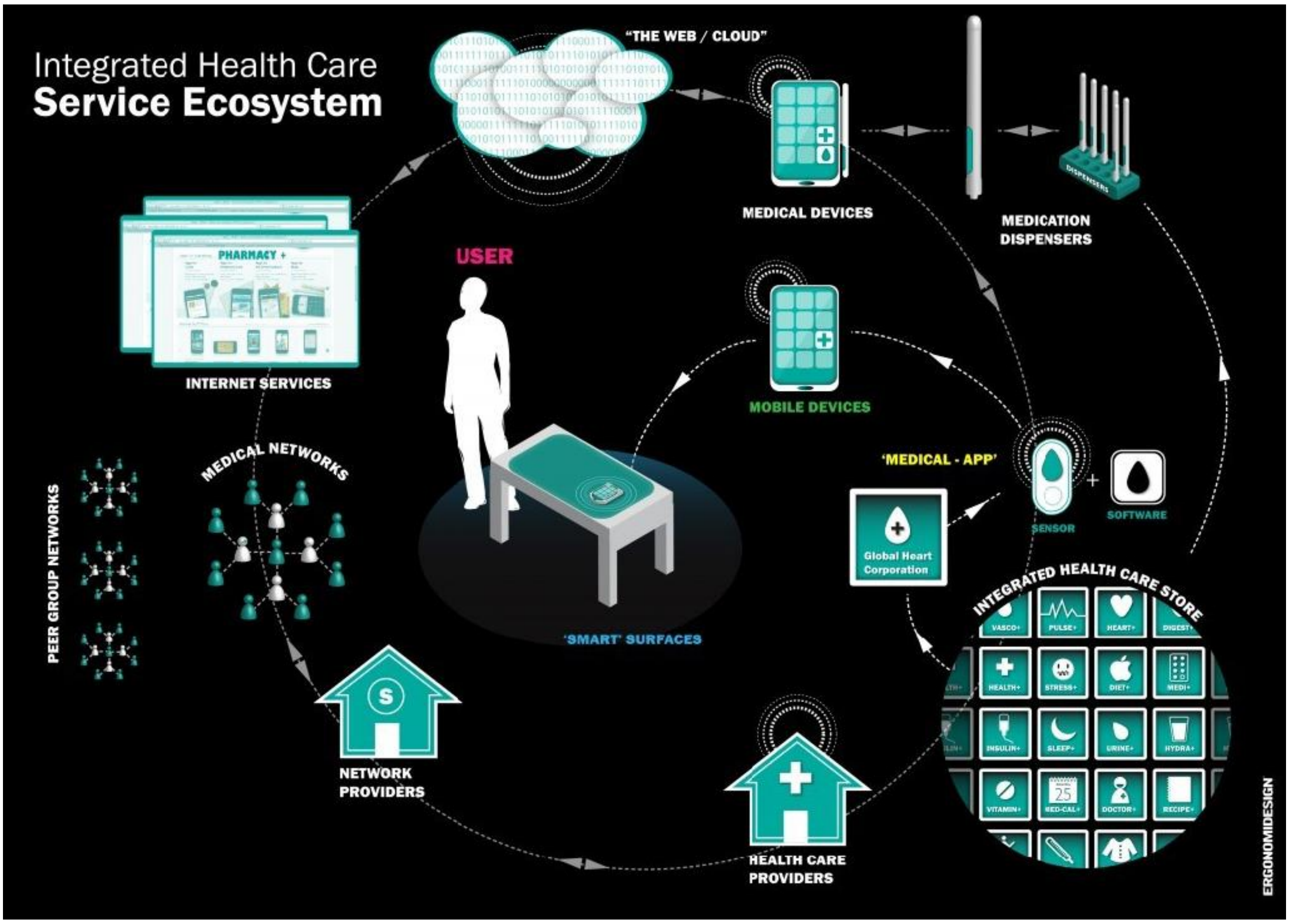

Figure 1. The envisioned health care service ecosystem of 2015 [10].

Figure 1, which has been excerpted from [10], shows a technology oriented view on what the future health care service ecosystem for the elderly might look like. There are multiple sources of health care information for consumption by a wide range of stakeholders (whom we refer to here as the inhabitants of the ecosystem). Such information can be generated by the inhabitants as well (e.g., medical practitioners volunteering their time in the community of interest). The health care information is packaged into services which can then be delivered through multiple platforms such as the Internet, smart mobile devices, and smart surfaces. These services can be stored in distributed locations or in cloud computing servers [11], which make it easy for them to be shared by other communities of interest. For certain types of services (e.g., remote monitoring and mobile health care), input information may also come from sensors and other medical devices designed to monitor the physiological conditions of the elderly in real-time. However, in our discussions of the health care service ecosystem, we focus on information health care which requires significant funding support.

Based on the roles played by the inhabitants of the health care service ecosystem, they can be classified into several species. These species occupy different places in the information value chain. One broad species of inhabitants is the information creators. They are generally medical practitioners or people who are well versed in certain domains of health care who volunteer their time and effort in creating knowledge in the health care service ecosystem for others to consume. Their role often involves three broad aspects: 1) creation of original contents for sharing and consumption; 2) reviewing contents created by peers in the ecosystem; and 3) answering questions raised by other inhabitants in the ecosystem. The other broad species of inhabitants is the information consumers. They are typically the elderly people or their family members who have the need to know more about health care related topics of interest. An individual can take up both of these roles and switch between them as demanded by the situation. For example, a retired doctor can act as an information creator when posting an article about Parkinson's Disease in the ecosystem. He can also be an information consumer when he asks others about issues regarding diabetes. Collaborations among information creators may be necessary from time to time to satisfy the needs of the information consumers.

There are multiple forces driving the evolutionary process in the health care service ecosystem. For instance, the commitment of information creators outside the health care service ecosystem may affect the amount of time and effort they can devote to the ecosystem. The most powerful force in such a complex system [12] is social norms [13]. The quality and promptness of information creation determines how valuable an information creator is viewed by inhabitants in the ecosystem. Such a perception can be thought of as his reputation in the environment, and may be used as a social capital to determine how his roles may evolve over time. The general level of adherence to the acceptable social norms in the ecosystem will affect how many inhabitants will stick to the ecosystem in the long run.

Existing Management Approaches

As computer-based systems become increasingly heterogeneous and interconnected, their complexity has increased significantly. They have become what researchers call digital ecosystems, which resemble biological ecosystems in many ways in terms of emergent behavior, self-organization, and evolution of dependence. In [14], [15], the authors gave examples of digital ecosystems and summarized them into an ecosystem architecture based on the service oriented architectural approach. Under such a system model, computing services can be dynamically re-combined into different operation sequences to achieve the objectives of different users.

For such a digital ecosystem to achieve long term sustainable operation, some form of management is needed. Distributed self-organization through evolutionary computing is a promising direction to pursue. In order to do so, it is necessary to first establish an appropriate metric to measure the competitiveness of a given configuration of a digital ecosystem during its evolutionary process. In [16], a metric named Physical Complexity has been proposed for this purpose. It provides a measure of information relative to randomness in the genomes in individuals by calculating the entropy of a given population in the digital ecosystem. In [17], several approaches (including genetic algorithm (GA) [18], neural networks (NNs) [19], and support vector machines (SVMs) [20]) have been compared to study how the collective intelligence of a given digital ecosystem population can evolve to solve complex problems.

It has been found that SVM based approaches performs better than others in terms of optimizing a digital ecosystem. Nevertheless, existing research in digital ecosystem management faces one important challenge: how to strike a balance between heavy handed management and leaving enough freedom for the inhabitants to interact on their own to allow emergent behaviors to form? In the case of [17], the ecosystem management approach essentially views the ecosystem as a closeknit team rather than an open system and dictates how they should evolve over time. Such an approach would not be useful in health care service ecosystems spontaneously formed by previously unrelated entities with potentially conflicting objectives.

II. Managing a Health Care Service Ecosystem

Basic Components

In order to allow the force of social norm to shape the health care service ecosystem, several key infrastructural elements must be present just like when managing a biological ecosystem [21]. They include:

- *Identity Management*: Secure and persistent identification techniques are the foundation for social norm mechanisms such as reputation to function. Without it, performance and behavioral information cannot be associated to individual inhabitants and the subsequent inferences cannot be carried out.
- *Ecological Modeling:* Knowing what to expect from a complex system is not a trivial task. Many environmental factors as well as individual characteristics of the inhabitants need to be taken into account. Ecological models, unlike engineering models, are rarely precise. However, they provide a useful reference frame to simply the complexity inherent in a trust ecosystem.
- *Attention to Temporal Context*: Time plays an important role in the relevance of observed behaviors of the inhabitants. Intuitively, more importance should be given to more recent interaction observations when forming a trust opinion. However, depending on the underlying system characters such as the past observed frequency of change in behavior patterns and the presence of collaboration among the inhabitants, the importance assigned to observations at different time may need to be dynamically adjusted.
- *Adaptability and Accountability*: The ecosystem management mechanisms need to co-evolve with the underlying environment in order to be effective. This requires a proper set of metrics to evaluate the impact of the management mechanism on overall system well-being. A monitoring

mechanism to measure these metrics and a feedback mechanism to adjust the key parameters of the mechanism to keep it relevant need to be the core part of the health care ecosystem management mechanism.

Each inhabitant in the health care service ecosystem has his/her own goals. These objectives can be conflicting at times. For example, a patient wanting to acquire information by consulting a medical expert through an online community of interest such as Healthbook [9] may wish to obtain detailed answers as quickly as possible. On the other hand, the medical expert may need to juggle multiple such requests while still carry out his official duty at work and find some personal time to relax with his family. If these conflicting goals are not managed properly, they can negatively affect the welfare of the inhabitants and reduce the efficiency and long term sustainability of the ecosystem, eventually resulting in the breakdown of normal operations.

Avoid Trying to Manage Everything

For such a complex system as a digital ecosystem, it is highly challenging to clearly define the overall system goals that must be achieved in order for the whole system to stay healthy. If the goals are defined too application dependent, the resulting management mechanism will lose its generality. On the other hand, if the goals are defined too general, they would not be actionable enough for designers to come up with appropriate management mechanisms. In this paper, we take a value-sensitive [22] approach to identify important general objectives of the two major inhabitant populations in the health care service ecosystem.

To maintain the long term sustainable operation of a health care service ecosystem, the ecosystem management mechanism needs to achieve the following objectives: 1) for information consumers: to help them obtain the most high quality information in the shortest possible amount of time; 2) for information creators: to direct information requests from information consumers to them in such a way that they are not over burdened with work in the ecosystem.

The exact dynamics of this process might be too complex to represent, as it needs to incorporate every action taken and every event that has occurred over the lifetime of the ecosystem. With more detailed considerations about the interactions between events, costs and probabilistic dependencies, etc., it might be too complex even to meaningfully write down. Nevertheless, the conflicting goals of Objectives 1 and 2 are similar to the situation described in a type of game called *Congestion Games* [23]. In such a situation, the quality and timeliness of an information consumer directing a request at an information creator *i* partially depends on how many other information consumers are directing their requests to *i* at the same time. To satisfy *Objective 1*, information requests should be completed by highly competent and reliable information creators as often as possible. However, as information creators are human beings and have limited time and capability, over concentrating requests to highly reliable people may cause longer elapses and negatively affect their morale. To achieve *Objective 2*, information requests should be divided more or less equally among the qualified information creators according to their real-time situation.

In order to express these objectives into a form that is suitable for computation, we first simplify the problem in view of the working mechanism of social norms. Modeling the individual situation facing each information creator and consumer is highly complex and will quickly run into scalability issues as the size of the ecosystem becomes large. Instead, we take a top-down approach to look at the overall achievement of Objectives 1 and 2 in a given health care service ecosystem using two system-level metrics we propose: risk and elapse, both of which should be minimized.

The risk aspect depends on a wide range of factors innate to each information creator *i*. We summarize them into key variables represented by the 3-tuple $\langle m_i(t), c_i^\tau(t), e_i^{max}(t)\rangle$. $m_i(t)$ denotes i's likely mood at time t (which can be easily reported by *i* using such online tools as the *Affectbutton* [24] to the ecosystem), $c_i^\tau(t)$ represents i's competence in providing useful information about a given topic τ (e.g., Parkinson's Disease), and $e_i^{max}(t)$ is the average total effort *i* can spend in the health care ecosystem as a volunteer per unit time (e.g., a day). $c_i^\tau(t)$ may be affected by

$m_i(t)$. $e_i^{max}(t)$ can be measured by the ecosystem through observing the behavior of i over time. The 3-tuple can be viewed as i's internal situation at a given time. $e_i^{max}(t)$ is assumed to be positively correlated with $m_i(t)$ subject to i's physical limitations.

To minimize the *elapse*, two conditions must be satisfied: 1) i's pending request queue $q_i^\tau(t)$ should not be allowed to grow indefinitely for all τ and *t*, and 2) $q_i^\tau(t)$ should not be too short (i.e., *i* is idling). Based on *i*'s internal situation, we can derive its target workload for each topic of interest $q_i^\tau(t)$ which positively correlates to $\langle m_i(t), c_i^\tau(t), e_i^{max}(t)\rangle$. Individually expressing the elapse of each request is a complex and inefficient approach to the problem. Instead, we derive a metric to measure the overall level of delay in the ecosystem that can be expected from a given configuration of pending request queues. We name this metric the collective drift away from the target workload of each information creator *i*. A large drift value indicates inefficiency in HIT allocation. Thus, to minimize *elapse*, the overall drift needs to be minimized. Thus, the objective of minimizing elapse is equivalent to minimizing the *drift* of the collective workload in a health care service ecosystem away from its collective target workload.

The properties of an information request *j* can be represented by the 3-tuple $\langle p^\tau, u^\tau, e^\tau\rangle$ denotes the priority/urgency of this type of requests and will affect their positions in the common request queue *Q(t)*. u^τ represents the utility that can be derived by the information consumer from successfully fulfillment of j on time. Both p^τ and u^τ can be indicated by the information consumer when submitting the request to the ecosystem. e^τ is the general expected effort that needs to be expended to complete j. We assume that the $\langle p^\tau, u^\tau, e^\tau\rangle$ values for all the information requests belonging to topic τ to be the similar. The risk that can be expected from letting *i* perform task *j* can, thus, be expressed as:

$$risk \equiv u^\tau(1 - c_i^\tau(t)). \tag{1}$$

The queuing dynamics for any pending task queue $q_i^\tau(t)$ is:

$$q_i^\tau(t) \leftarrow \max[q_i^\tau(t-1) + a_i^\tau(t-1) - \mu_i^\tau(t-1), 0] \tag{2}$$

where $a_i^\tau(t)$ denotes the number of new requests under topic τ assigned to $q_i^\tau(t)$ at time *t*, $\mu_i^\tau(t)$ is the number of requests from $q_i^\tau(t)$ fulfilled by *i* at time *t*. The max[· ,0] operator ensures that the size of the queue will never be negative. *Drift* is positively correlated to both $a_i^\tau(t)$ and $\mu_i^\tau(t)$ (i.e., increase in either of them causes the *drift* to increase). Based on the principle of *Lyapunov drift* [25], we have:

$$drift \equiv a_i^\tau(t) \cdot \mu_i^\tau(t). \tag{3}$$

Eq. (3) can be trivially minimized by assigning both $a_i^\tau(t)$ and $\mu_i^\tau(t)$ to 0 for all *i*, τ and *t* (i.e., all information creators stay idle all the time). However, this is not a valid solution in practice. Through the above analysis, we can formalize the objective of managing a health care service ecosystem as:

Minimize: $$\frac{1}{T}\sum_{t=0}^{T-1}\sum_{i,\tau} a_i^\tau(t)[\varphi \cdot u^\tau \cdot \left(1 - c_i^\tau(t)\right) + \mu_i^\tau(t)] \tag{4}$$

Subject to:

$$\sum_\tau (a_i^\tau(t) \cdot e^\tau) \le e_i^{max}(t) \tag{5}$$

$$0 \le a_i^\tau(t) \le \lambda_i^\tau(t) \text{ for all } i, \tau, \text{ and } t \tag{6}$$

where $\lambda_i^\tau(t)$ is the number of new requests under topic τ being added into the common queue *Q(t)* by the information consumers at time *t*, and φ is a weight variable indicating the relative importance given to *risk* and *drift* while minimizing Eq.(4).

Promising Future Research Directions

With this formalization, finding solutions for all $a_i^\tau(t)$ whenever new requests are proposed so as to minimize Eq.(4) subject to Constraints (5) and (6) would be technically possible. These solutions should be able to form a basic ecosystem management mechanism to maintain the stability and efficiency of the health care service ecosystem. Nevertheless, based on the foundation of this formulation, many exciting research directions can be explored to further enhance the user experience of various inhabitants in the ecosystem.

Information creators and information consumers may possess different utility functions with regard to the fulfillment of the same information request. The information consumers' utility functions tend to be linearly related to the number of high quality answers to they can obtained from the ecosystem. The more such answers they can obtain, the more willing they will become to stay in a health care service ecosystem. However, this may not be the case for information creators who are essentially as volunteer workers. The level of satisfaction derived from serving the information consumers may increase with the number of successfully fulfilled requests initially. However, this may stop being the case once they feel being burdened by such requests. In this situation, the utility function for the information creators may not be linear. Although incentive mechanisms [26] can be designed in an attempt to make information creators' utility functions linear for longer period of time, solutions to Eq.(4) must take into account of the existence of both types of utility functions [27] to help information creators to maintain work/life balance [28].

Recommendations made for the elderly information consumers should take into account their special preferences when obtaining information from a health care service ecosystem which is an open and dynamic environment characterized by uncertainty (e.g., which information source is trustworthy?). Research insights from socioemtional selectivity theory [29] may offer a useful starting point for designing information request distribution mechanisms whose decisions make sense to the elderly. The solution to Eq.(4) should also take into account the situations where the recommendations are not fully complied by information consumers in accordance to the bounded rationality theory [30] under the game theoretic framework.

III. Conclusions

In this paper, we analyzed the challenges facing a vision for future health care service ecosystems manned by volunteers to serve the information needs of the elderly and their loved ones. We discussed the needs for viewing such systems as digital ecosystems and the importance for careful management of such systems to ensure their long term sustainability. We proposed a novel approach to view the core functionality of such an ecosystem as a queuing system and formalized the problem of ecosystem management as a constraint optimization problem. The proposed ecosystem management objective function contains only metrics for the general wellbeing of a health care service ecosystem, and leaves it to the inhabitants to autonomously determine how they wish to utilize the services in the system or organize themselves to achieve common goals. Under such a problem formulation, we provided a vision for important future research issues that are worth further investigation.

Acknowledgements

This research is supported in part by Interactive and Digital Media Programme Office, National Research Foundation hosted at Media Development Authority of Singapore (Grant No.: MDA/IDM/2012/8/8-2 VOL 01).

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