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Knowledge management in healthcare: towards 'knowledge-driven' decision-support services

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Abstract

In this paper, we highlight the involvement of Knowledge Management in a healthcare enterprise. We argue that the 'knowledge quotient' of a healthcare enterprise can be enhanced by procuring diverse facets of knowledge from the seemingly placid healthcare data repositories, and subsequently operationalising the procured knowledge to derive a suite of Strategic Healthcare Decision-Support Services that can impact strategic decision-making, planning and management of the healthcare enterprise. In this paper, we firstly present a reference Knowledge Management environment—a Healthcare Enterprise Memory—with the functionality to acquire, share and operationalise the various modalities of healthcare knowledge. Next, we present the functional and architectural specification of a Strategic Healthcare Decision-Support Services Info-structure, which effectuates a synergy between knowledge procurement (vis-à-vis Data Mining) and knowledge operationalisation (vis-à-vis Knowledge Management) techniques to generate a suite of strategic knowledge-driven decision-support services. In conclusion, we argue that the proposed Healthcare Enterprise Memory is an attempt to rethink the possible sources of leverage to improve healthcare delivery, hereby providing a valuable strategic planning and management resource to healthcare policy makers. © 2001 Elsevier Science Ireland Ltd. All rights reserved.

Keywords: Knowledge management; Data mining; Decision-support; Healthcare enterprise memory; Strategic decision-support services; Healthcare delivery info-structure

1. Introduction: knowledge management in healthcare

Knowledge Management (KM) in healthcare can be regarded as the confluence of formal methodologies and techniques to facilitate the creation, identification, acquisition, development, preservation, dissemination and finally the utilisation of the various facets of a healthcare enterprise's knowledge assets [1–3].

The health care industry has evolved into an extended enterprise—an enterprise that is powered by sophisticated knowledge and information resources. In today's knowledge-theoretic healthcare enterprises, knowledge is deemed as a 'high value form of information' [4] which is central to the enterprise's 'capacity to act' [5]. The field of knowledge management provides the methodological and technological framework to: (a) pro-actively capture both the *experiential knowledge* in-

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trinsic to what are we doing vis-à-vis healthcare practice and delivery, and the *empiric*al *knowledge* derived from the outcomes of what have we done; and (b) operationalise healthcare knowledge to serve as a strategic decision-making resource, vis-à-vis an ensemble of business rules, trend predicting insights, workflow analysis, analytic outcomes, procedural guidelines and so on [6].

Healthcare enterprises can be regarded as 'data rich' as they generate massive amounts of data, such as electronic medical records, clinical trial data, hospitals records, administrative reports, benchmarking findings and so on. But, in the same breath we can say that healthcare enterprises are 'knowledge poor' because the healthcare data is rarely transformed into a strategic decision-support resource. For that matter, with the emergence of technologies such as KM and Data Mining (DM) [7], there now exist opportunities to facilitate the migration of raw empirical data to the kind of empirical knowledge that can provide a window on the internal dynamics of the healthcare enterprise. We argue that such data-derived knowledge can enable healthcare managers and policy-makers to infer 'inherent', yet invaluable, operative principles/values/know-how/strategies pertinent towards the improvement of the operational efficacy of the said healthcare enterprise.

We contend that the operational efficacy of a healthcare enterprise can be significantly increased by (a) procuring diverse facets of empirical knowledge from the seemingly placid healthcare data repositories, and (b) by operationalising the procured empirical knowledge to derive a suite of packaged, value-added *Strategic Healthcare Decision-Support Services* (SHDS) that aim to impact strategic decision-making, planning and management of the healthcare enterprise [8,9]. The vantage point of the aforementioned SHDS is that they provide strategic insights/recommendations/predictions/analysis to assist healthcare managers/policy-makers/analysts to device policies or make strategic decisions or predict future consequences by taking into account the actual outcomes/performance of the healthcare enterprise's current operative values—which may not necessarily be the same as the espoused operative values.

To meet the above objectives, we propose to design a KM-oriented info-structure, based on a novel approach that effectuates a synergy between knowledge procurement (via DM) and knowledge operationalisation (via KM) techniques. The modus operandi of the proposed synergy is as follows: DM techniques are used to 'mine' healthcare data repositories to inductively derive decision-quality healthcare knowledge, whereas KM techniques are subsequently used to operationalise the inductively derived healthcare knowledge to yield a suite of SHDS. The description of the functional and architectural specification of such a KM-oriented info-structure is the theme of the work reported here. In this paper we will present:

A reference KM info-structure—a *Healthcare Enterprise Memory (HEM)*—that purports the functionality to acquire, share and operationalise the various modalities of knowledge existent in a healthcare enterprise [2,10].

A demonstration *SHDS Info-structure* that leverages existing healthcare knowledge/data bases to (a) derive decision-quality knowledge from healthcare data and (b) generate and deliver a variety of SHDS [6]. Here, we will discuss the end-user perspective of the SHDS info-structure as opposed to technical details.

The work reported here derives from our present interest in the Malaysian Tele-Medicine initiative [11,12] under the auspices of the *Multimedia Super Corridor* project.

2. Strategic healthcare decision-support services: an overview

The effective delivery of healthcare services hinges on the ability to deliver appropriate, proactive and value-added services to different client segments on a timely basis. In general, healthcare services need to be systematically determined based on needs; packaged according to usage patterns, demographics and behavioural psychographics; and delivered in a ubiquitous, proactive and continuous manner. These mutually inter-related constraints are hard to formulate, let alone satisfy, using conventional strategic planning techniques. Henceforth, for enhanced healthcare services efficiency and informed strategic planning and management, there is an imminent need to model and measure healthcare processes using definitive healthcare process models that are inductively derived from the collected healthcare data. We propose that the controlled simulations of data-derived healthcare process models can be effectively used to derive 'knowledgeable' (strategic) insights about the intrinsic behaviour of the healthcare enterprise. The rationale of the approach is that by understanding what worked—or did not—healthcare practitioners can identify areas for improvement and/or capitalise on past successful methods.

SHDS can best be defined as a suite of knowledge/data-driven, strategic, decision-support services derived from both healthcare data and the health enterprise's knowledge bases, with the objective to improve the delivery of quality healthcare services (see Fig. 1 for a typical SHDS environment). Methodologically speaking, SHDS cater for the migration of *data* (the what), through a sequence of sophisticated operations to *information* (the trend or behaviour) to *knowledge* (the why) to the ultimate level of *wisdom* (the

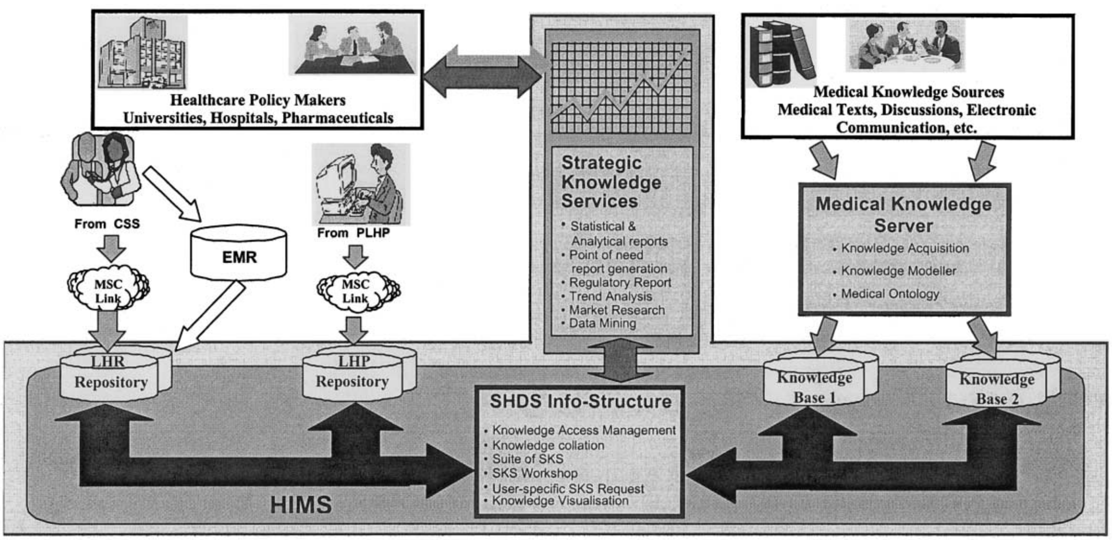

Fig. 1. An overview of a SHDS environment.

Table 1
A synopsis of the proposed SHDS

Main SHDS	Specific SHDS
1. Analysing trends in hospital admission	▪ Spectrum of disease ▪ Seasonality in disease pattern ▪ Intervention measures to be instituted
2. Analysing treatment pattern	▪ Comparison between hospitals and within hospitals ▪ Auditing against acceptable localised treatment consensus ▪ Criteria for admission ▪ Investigations ▪ Therapeutic intervention
3. Analysing outcomes of treatment	▪ Gauge standard and quality of care ▪ Enhancing Health System Research ▪ Highlight aberrations in treatment outcomes ▪ Develop norms/ standard of outcome measures acceptable to local realities
4. Analysing cost-effectiveness of health care	▪ Audit expenditure and income ▪ Highlight areas to focus ▪ Allows manpower planning ▪ Allows planning for infrastructure development
5. Planning out-of hospital (ambulatory) care	▪ Assessing client (patient's and relative's satisfaction ▪ Allows plan of care after discharge to be made ▪ Monitor treatment after discharge and out patient's management
6. Forecasting 'new disease' and strategising appropriate preventive measures	▪ Warm health planners of impending epidemics ▪ Allows appropriate preventive strategies to be recommended at community level ▪ Better public education strategies
7. Forecasting complications of treatment	▪ Hospital acquired infection ▪ Drug resistance pattern ▪ Iatrogenic diseases
8. Forecasting the spread of infectious diseases	

necessary actions to be taken). The innovative meta-level of wisdom provides an additional dimension to SHDS where, the data collected, the information determined, the knowledge acquired can be used towards the subtle shaping of the healthcare enterprise so as to acquire the highest degree of healthcare quality by either fine-tuning the existing enterprise-wide practices or by defining new action plans for policy making and health planning [9,12].

Typical SHDS may include: trend analysis of diseases/epidemics [13,14], treatment patterns, hospital admissions, drug patterns and so on, benchmarking and best-practices reporting, outcomes measurement, what-if scenario analysis; comparing medical practices with medical business rules, market research, feedback routing to R&D institutions (e.g. drug effectiveness on outcomes of treatment); data analysis for healthcare financing, health surveillance and resource allocations [9].

Table 1 gives an abridged list of possible SHDS. Principal beneficiaries of SHDS are envisaged to be the Ministry of Health (MoH), pharmaceuticals, medical service organisations, private health providers, universities, and community health organisation.

3. The healthcare enterprise memory

The *Healthcare Enterprise Memory (HEM)* can be characterised as a conglomerate KM architecture—comprising functionally independent computing systems—that provides the functionality to acquire, share, reuse and operationalise the various modalities of healthcare knowledge (e.g. tacit and explicit knowledge of healthcare practitioners, healthcare related documents, data, processes, workflows, experiences and lessons learnt). The technical realisation of HEM involves a confluence of data, information and knowledge management technologies that in unison aim to operationalise healthcare knowledge so as to realise a suite of SHDS. Typical services offered by HEM may support healthcare planning and management, automatic dissemination of knowledge, reuse of knowledge and experience, support of intelligent knowledge management services, timely provision of knowledge and experience, transforming information to action, connecting and converting knowledge and above all healthcare (meta) modelling [1,2] [15]. On an operational note, HEM is a consequence of the need to explicate the abstract semantics of healthcare knowledge. On a functional note, the HEM allows for the synchronisation of the heterogeneous healthcare knowledge resources to yield a common goal—i.e. the realisation of a dynamic, progressive and pro-active healthcare enterprise. We briefly identify the four functionally distinct layers of our proposed HEM (see Fig. 2):

1 *Object Layer:* Consists of various healthcare information and knowledge sources such as data-, document-, knowledge- and scenario-bases.

2 *Knowledge Description Layer:* The main purpose of this layer is to facilitate the accurate selection and the efficient access to relevant object-level healthcare knowledge in a given application situation. Medical ontologies reside at this layer to (a) maintain a standard vocabulary to describe concepts and relationships between entities that attempt to share knowledge [16,17] and (b) facilitate the incremental scaling-up of healthcare knowledge.

3 *Application Layer:* Models and executes various healthcare processes and tasks, realised in different ways ranging from dedicated programs to flexible query interfaces.

4 *Services Layer:* Provides specialised healthcare services through the use of various dedicated applications [8,9].

In this paper, we will focus on just one component of the HEM, which is the SHDS info-structure (shown as the shaded area towards the right side of Fig. 2).

3.1. The SHDS info-structure

We understand that the healthcare domain is replete with many DM applications and solutions, but we contend that most efforts, by and large, are limited to specialised and focused problems that are handled by a pre-selected DM algorithm [18–21]. Another noticeable limitation with such efforts is that the onus is on the user to define a model of the data—the user is required to select the input data source, the relevant data attributes, the pertinent DM algorithm(s) and finally the most appropriate data visualisation format—in order to derive actionable knowledge from the collected data. Indeed, this places too much demand on a novice user, who is merely interested in the automated generation of 'just-in-time' strategic decision-support knowledge. To address the above limitations, we have developed a generic, modular and query-driven decision-support SHDS-info-structure that incorporates an ensemble of DM techniques to 'mine' heterogeneous healthcare data repositories to derive 'just-in-time' decision-quality (healthcare) knowledge in response to specific user-requests.

4. The SHDS info-structure: architectural details

The key to the generic functionality of our SHDS info-structure is the implementation of a wide range of pre-packaged, yet user customisable, query-driven DM solutions or *modules*, each with pre-defined functionality. The DM modules are designed to interact with users to acquire the specification of the problem and in return provide decision-support services. Technically, the use of *Distributed Object Technologies*—i.e. middle ware technologies such as CORBA, ActiveX and JavaBeans [22]—allow users to (a) read-

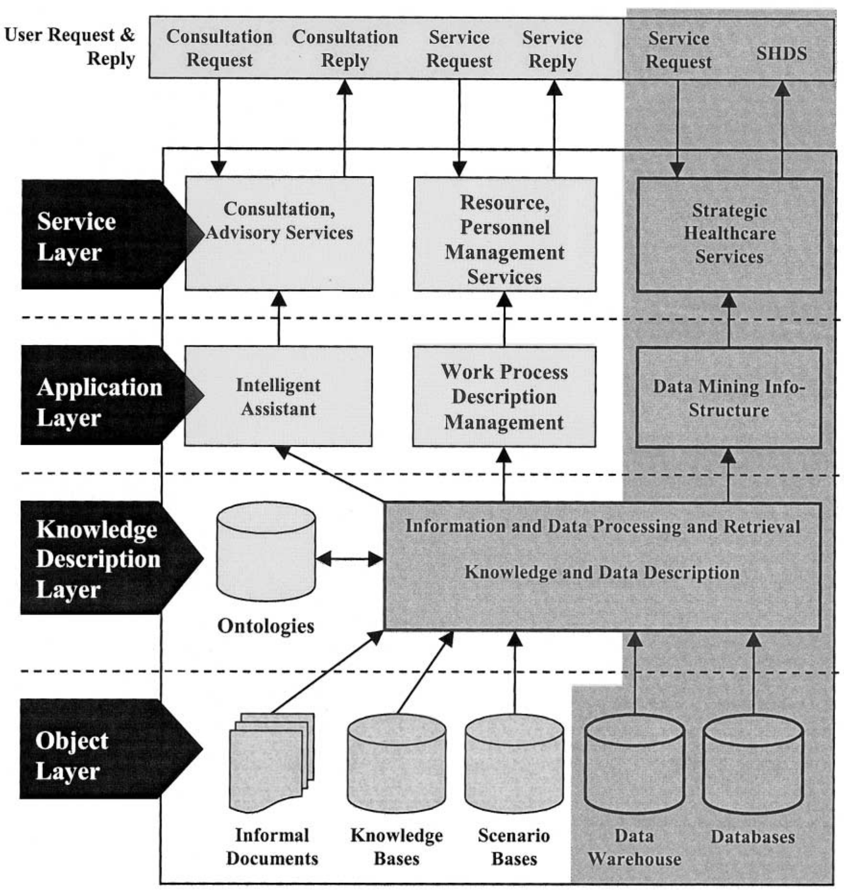

Fig. 2. The healthcare enterprise memory model.

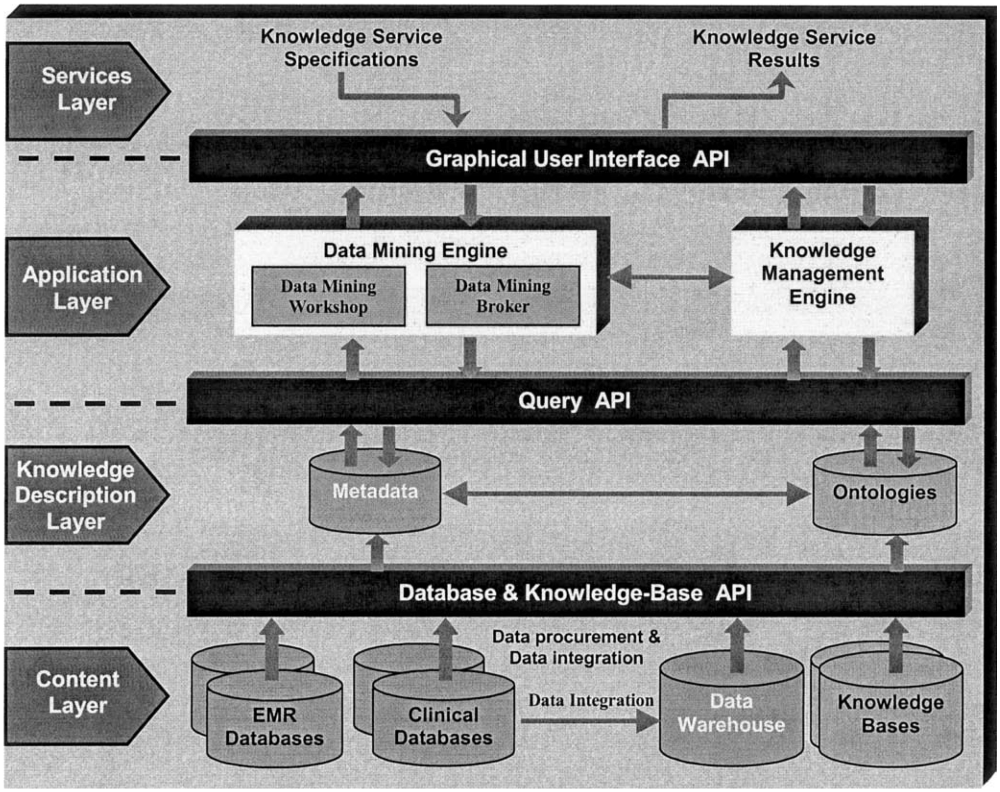

Fig. 3. An overview of the multi-tier functional architecture of the SHDS info-structure.

ily select the most pertinent DM module (in terms of functionality) for the problem at hand; (b) present the problem specification (as per the internal specification language) to the DM module; and (c) customise the pre-packaged DM module as per the problem specification to generate the desired SHDS.

The stratified design of the SHDS info-structure is based on the following principles: (i) a user-friendly and cognitively transparent top-level user interface for the specification of a decision-support service and the visualisation of the DM outcome; (ii) a library of functionally diverse DM modules that cover the entire spectrum of decision-support services deemed relevant to the healthcare domain; (iii) a service customisation facility to generate specialised; and (iv) a rich source of healthcare data vis-à-vis health databases and data warehouses.

Conceptually, the SHDS info-structure has a multi-tier architecture that effectuates a confluence of KM and DM techniques (shown in Fig. 3 and further elaborated in Fig. 4). If we look at Fig. 3, the lowest layer is the *Content Layer* which comprises the content sources—healthcare databases, data warehouses and knowledge bases. The second layer—the *Knowledge Description Layer*—provides both an abstraction and specification of the data and knowledge resources in terms of metadata and ontologies, respectively. The third layer—*the Application Layer*—is the core layer which consists of two engines, one geared towards DM tasks whilst the other handles KM tasks. Finally, the top layer—the *Services Layer*—serves as the user-interface, allowing users to select and specify the SHDS required and to receive the results/findings/conclusions/recommendations. The multi-tiered architecture presented here offers several key advantages. Firstly, data issues such as data cleansing, integration and consolidation are taken care of at the system level. Secondly, the use of APIs to connect the various inter-layer components allows (a) seamless message and data passing;

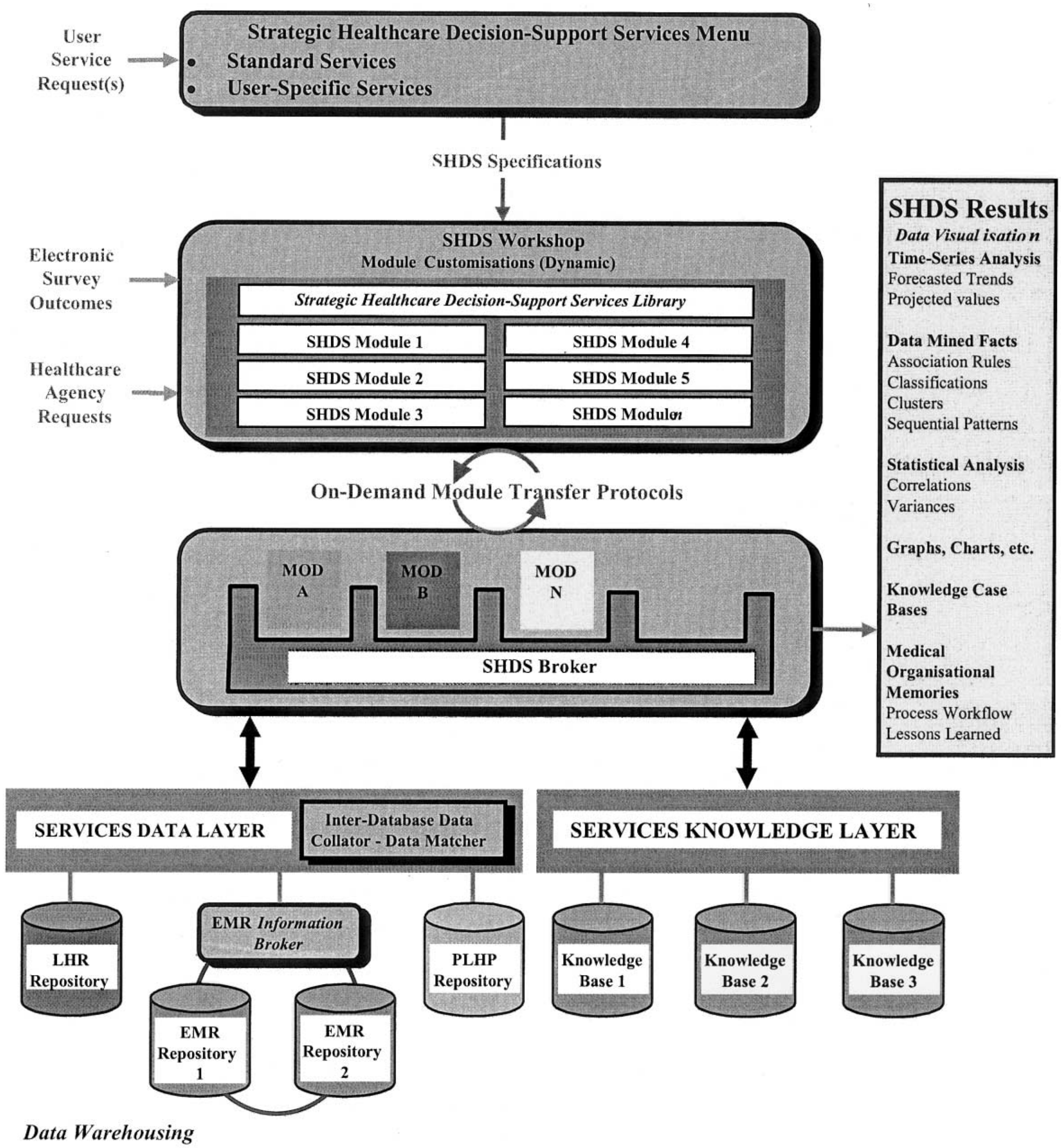

Fig. 4. The architecture of the SHDS info-structure.

(b) on-line and interactive selection of DM functions and customisation of modules, whilst maintaining the constraints and protocol requirements at each level. We now briefly describe the functional characteristics of the various components of our SHDS info-structure. Fig. 4 gives the architecture of the SHDS info-structure.

4.1. SHDS modules

An all-encompassing solution that meets the diverse decision-support needs of a healthcare enterprise is achieved by the implementation of a number of individual, self-contained, specialised DM modules, each designed to provide a particular SHDS. For instance, three SHDS (1) analysing the trends in hospital admission (2) analysing the trends in treatment patterns and (3) analysing the trends outcomes of treatment, will be implemented as three individual SHDS-modules. The SHDS modules are implemented as an integration of 'standard task-codes' stored in libraries specific to tasks ranging from data collection to DM algorithms. In technical terms, each SHDS is written as a script in a high-level declarative DM language (comparable to SQL). The script specifies the following characteristics of the SHDS: (a) the minable view—the data resources to be mined, more specifically the part(s) of the database(s) to be mined; (b) the attributes of the data to be used, together with their significance values and relational information, in any; (c) the DM algorithm(s) to be used; (d) the type of patterns/rules to be mined; (e) the properties that the chosen pattern should satisfy; (f) the constraints imposed to reflect the user's intentions and the peculiarities of the SHDS; and (g) the data visualisation method to be used to display the DM results.

The design of SHDS as modules predicates the provision of specifying external constraints, over and above the designated functionality of a SHDS, in order to customise the inherent processing of a SHDS module according to the specific user demands. This is akin to constraint-based DM, as reported in the DM literature [23]. At a high-level, the constraints implemented within the SHDS modules are divided into six broad categories [23]:

1 *Knowledge Constraints* specify the type of healthcare knowledge to be mined. For instance, association rules, classifications, clusters, sequential patterns, concept descriptions and so on. This is the primary constraint as its definition determines the nature of subsequent constraints.

2 *Data Constraints* specify the set of data—the origin of the databases, the relevant features and relationships between data items—relevant to the selected SHDS. Such constraints are usually represented as SQL queries to databases.

3 *Dimension/Level Constraints* specify the dimensions or levels of data to be examined in a database. Such constraints are usually applicable in concert with multidimensional databases.

4 *Rule Constraints* specify certain rules, pertaining to the patterns being discovered, that need to be observed whilst mining the data. Such constraints have a controlling and filtering behaviour.

5 *Interestingness Constraints* specify the degree of usefulness or interestingness (statistical point of view) of the knowledge being discovered. Typically, if the knowledge being is deemed less interesting vis-à-vis the requirements of the SHDS then it is ignored.

6 *Qualitative Constraints* specify measures to examine the validity and correctness of the derived knowledge item.

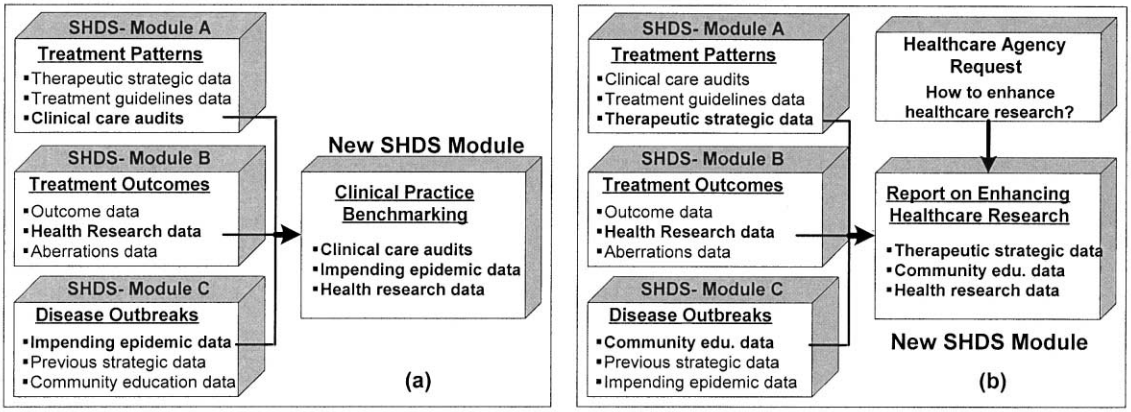

Fig. 5. (a) The generation of a new SHDS-module by combining the data elements from multiple existing SHDS-modules. (b) The generation of a new SHDS-module in response to a request from a healthcare agency.

4.2. Strategic healthcare decision-support services menu

SHDS-Menu is the GUI application for the specification of a SHDS via two modes: (1) The user may choose a pre-defined SHDS, and (2) The user may 'design' a specific SHDS.

4.3. Strategic healthcare decision-support services workshop

The *SHDS-Workshop* is an application environment that supports: (1) the storage of all SHDS modules in the *SHDS Library;* and (2) the generation of demand-specific, new SHDS modules by the *Module Customisation Workbench*. The SHDS-Library stores a suite of SHDS modules, with the functionality to add new SHDS modules without disturbing the internal dynamics of the available SHDS-modules. The Module Customisation Workbench caters for the 'dynamic' generation of specialised SHDS modules as per user requests by: (a) Mixing existing SHDS-modules in some principled manner to realise a 'hybrid' SHDS-module (shown in Fig. 5a). In this case, either entire modules are synthesised or else specific elements of each module are synthesised (note there exist certain constraints to the synthesis of modules); and (b) Customisation of existing SHDS to derive user-specific services (shown in Fig. 5b).

4.4. Strategic healthcare decision-support services broker

The SHDS-Broker is the system to dynamically 'mix and match' multiple existing SHDS-modules to deliver innovative, 'need-of-the-hour' services customised according to the user requirements. Architecturally, the SHDS-Broker comprises a number of independent 'slots', where each slot can be filled by a SHDS-module. The eventual SHDS generated by the SHDS-Broker derives from the systematic amalgamation of the multiple SHDS-modules within the different slots (see Fig. 4). Design issues addressed here are: (i) scheduling protocols for each module to access the services data and services knowledge layers; (ii) the 'hooks' to assimilate the modules in the slots; (iii) the sequence in which the modules will be visited by the processing engine; (iv) the compilation of the analysis by each module to generate a global report.

4.5. Services-data layer

The Services-Data layer is responsible for delivering the required data from the data bases and data warehouse(s) to the SHDS-Broker. *Information Broker* [24] is a data access application to collect and collate relevant information from the multiple and heterogeneous healthcare data repositories.

4.6. Strategic healthcare decision-support services visualiser

The SHDS-Visualiser implements a combination of SHDS (result) visualisation formats, such as graphs, tables, maps, abstract maps and visualisation hypercubes.

4.7. SHDS delivery

Two intuitive, easy-to-use, visual applications are designed to deliver the SHDS: (1) On the Internet and (2) Direct Links to SHDS info-structure, which will be Insurance and Pharmaceutical companies, hospitals and govt. agencies.

5. Predictive modelling of bacteria-antibiotic sensitivity and resistivity patterns: an exemplar strategic healthcare decision-support service

Here we present an exemplar SHDS implemented as an individual module in the SHDS info-structure. The purpose here is not to give the technical details of the SHDS, rather to highlight its end-user perspective—i.e. its origination, functionality and decision-support information.

Nature of Service: The scope of the SHDS is to provide effective infectious-disease epidemic risk management [13,14]. The decision-support knowledge provided by this SHDS is characterised as the predicted *future* effectiveness of candidate antibiotics towards a bacteria. Effective infectious-disease epidemic risk management services can benefit from this knowledge by increasing the usage of effective antibiotics during the projected time period, whilst at the same time avoiding the usage of the 'ineffective' antibiotics.

Data Collection: The bacterial sensitivity/resistivity data was provided by Universiti Sains Malaysia Hospital located in Kota Baharu, Malaysia. This data-set compiled over six years (1993–9198) comprises data on the sensitivity/resistivity of 89 organisms, for which 36 different antibiotics were prescribed.

Implementation of the SHDS: A Back-Propagation Neural Network (BPNN) was used to perform the core DM task—the BPNN was simply taught historical bacterial sensitivity/resistivity data of the time-series and the learnt BPNN is used to predict future bacterial-antibiotic sensitivity. In functional terms, this SHDS module requires three past sensitivity/resistivity Bacteria-Antibiotic (BA) values ($i = -3, -2, -1$) and the present ($i = 0$) to generate three future sensitivity/resistivity BA values ($i = 1,2,3$).

End-User Functionality of the SHDS: This particular SHDS is made accessible to healthcare practitioners via a WWW interface. The workflow is as follows: (i) the user needs to specify the bacterial organism, the list of possible interacting antibiotics whose effectiveness is being examined, the nature of the forecast profile to be generated, and the predictive time frame (as shown in Fig. 6a); (ii) the selected SHDS performs the necessary DM activities on the available data; and finally (iii) the forecasted results are displayed on a dynamically generated Web-page (as shown in Fig. 6b).

6. Features of the SHDS info-structure

Functionally, the proposed SHDS info-structure not only meets the specific demands for SHDS, but extends further to add value by way of supporting a number of attractive features, such as:

Data Collation: Comprehensive data analysis by collating data from multiple data repositories to form a virtual, seamless and continuous data source.

Suite of Strategic Decision-Support Services: A wide range of SHDS, categorised into four prominent classes: (1) Treatment Management; (2) Pharmaceutical Requirements; (3) Healthcare Planning and Services and (4) Best Practices Benchmarking.

User-Specific Decision-Support Service Requests: To cater for usage preferences and temporal constraints, we allow users the flexibility to customise existing SHDS modules to meet user-specific decision-support requests.

Addition of New Decision-Support Services: Dynamic addition of new SHDS-modules to the existing SHDS info-structure is possible without disturbing the existing SHDS-modules.

Multiple Data & Knowledge Analysis Techniques: A confluence of functionally diverse data analysis methodologies realise the generation of a variety of decision-support services, such as data mining, statistical analysis, symbolic rule extraction, time-series forecasting and benchmarking.

Multiple Result Visualisation Methods: Multiple results visualisation formats, ranging from graphs to 3D hypercube maps to active reports/documents can be selected by the user.

7. Concluding remarks

For all practical purposes, modern healthcare systems generate massive amounts of ‘knowledge-rich’ healthcare data, but unfortunately this asset is not yet fully ‘cashed’ for improving the management and delivery of healthcare services. In this paper, we have suggested that the possible synergy of *KM* and *DM* techniques can provide opportunities for the generation of strategic knowledge-driven decision-support services from the seemingly ‘mundane’ healthcare data. The

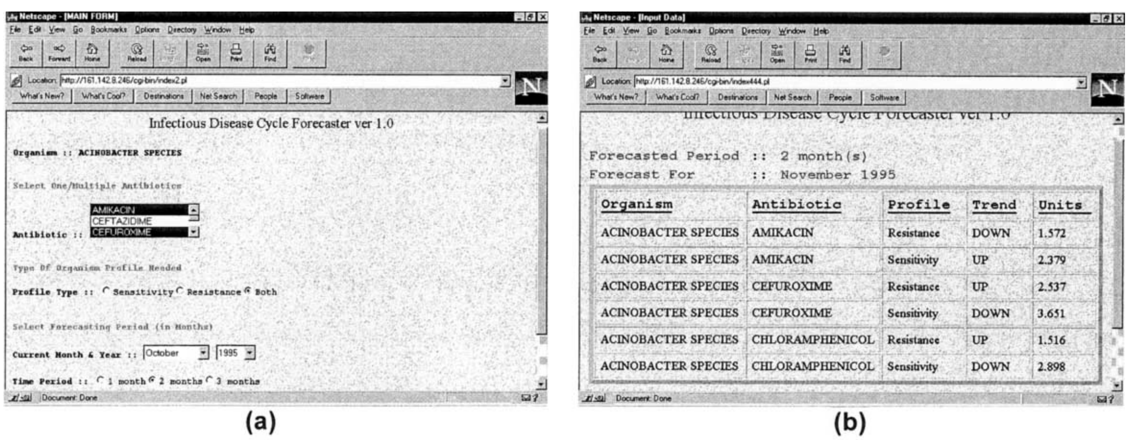

Fig. 6. (a) The main screen for the specification of the SHDS. (b) Forecast report for an exemplar bacteria-antibiotic interaction.

general idea is to leverage the healthcare enterprise's databases, data warehouses and knowledge bases to derive experiential knowledge from it, which can in turn be used to optimise strategic decision-making and planning. We have proposed a viable IT info-structure—the so-called SHDS info-structure—that can facilitate the automated transformation of healthcare data to a suite of heterogeneous strategic knowledge services. More importantly, the HEM provides an opportunity to migrate healthcare practice rules, primarily stated in texts, towards the generation of value-added, pro-active strategic services that may directly impact the behaviour and efficacy of the healthcare enterprise as a whole. In conclusion, we emphasise that the conception of the both the HEM and the SHDS info-structure has identified opportunities to improve healthcare management through the increased use KM technology. The HEM project is still under development, in particular the focus of the on-going work is the acquisition of tacit knowledge [25] and the creation of a variety of medical knowledge bases.

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