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Development of an Intelligent Laboratory Information System for Community Health Promotion Center

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Abstract

This study aimed to develop an Intelligent Laboratory Information System (ILIS) for the community health promotion center in Kwachun city to help process an increasing number of laboratory test data in an efficient manner, and to support the clinical decision-making of public health doctors. A sample of 170 cases was used for validation of the system. Overall, the system correctly predicted 92.5% of the cases. This paper also analyzed the economic feasibility of the ILIS based on the Information Economics approach. The results showed that the ILIS not only helps screen more people by increasing the capacity of a health promotion center, but also brings in more revenue to the center.

Keywords:

Laboratory information system; Rule-based reasoning; Intelligent system; Community health promotion

Introduction

The Korean government has been actively taking the initiative in introducing a health promotion movement by enacting the Health Promotion Law in 1995. The focal point of such activities is to strengthen the capability of the community health promotion center in delivering health promotion services, such as mass screening programs and health education.

While the screening program had a positive impact on improving the health status of community residents, it also significantly increased the workload of the health promotion center staff because of the increasing amount of paperwork generated by laboratory tests. This also created problems in interpreting laboratory test results because of the absence of a clinical pathologist in most of the health centers.

Innis [1] suggested that a laboratory-based computer diagnostic system could aid the clinician in solving such problems by interpreting hematological and biochemical data and providing a list of possible diagnoses. There have been several studies on laboratory information systems for providing diagnostic information. They are classified into three categories: a) ordering laboratory tests [2], b) interpretation of test results [3], and c) ordering for drug doses [4]. However, most of such systems rely only on laboratory data, not utilizing the patient's lifestyle information (e.g. smoking, drinking, family history, etc.), and therefore they have a limited capability of providing comprehensive diagnostic as well as therapeutic advice.

In this study, an Intelligent Laboratory Information System (ILIS) was developed to process an increasing number of laboratory data that would reduce the workload of laboratory technicians and to support the clinical decision-making of doctors. The ILIS was evaluated in terms of its clinical validity as well as economical feasibility.

Subjects and Methods

Subjects

A total of 170 residents who had visited the Kwachun health promotion center for screening from May 1 to May 31, 2000 were used to validate the system.

Knowledge Model

The ILIS was developed by a rule-based reasoning model using the Intelligent Rules Element (IRE) which is an object-oriented tool (Neuron Data, Inc). A total of 57 rules were used to predict diagnosis. The rule-based model was validated by comparing its predicted diagnosis with the actual diagnosis and the final diagnosis which was made after considering various information. The rule-based model consists of 44 objects (e.g. hepatoma, cirrhosis, etc.), 11 classes (e.g. liver and kidney diseases, etc.), and 186 properties (89 lab test items and 97 patient lifestyle items).

The patient lifestyle items were categorized into the following 6 groups: smoking, drinking, family history, past history, exercise, and diet.

Economic Analysis

Economic evaluation of the system was performed based on the information economics (IE) methodology [5]. In IE, traditional *benefits* are expanded by *value* to quantify them systematically by including the following values. *Direct benefit* from using the ILIS was the reduced personnel costs by automating laboratory data processing, such as a test order entry, result interpretation, prescription, and entry of the test results. *Value acceleration* is an improved performance of a system for speeding up the flow of information. In ILIS, the increased revenue from one additional person per day for screening due to the reduction of laboratory data processing time falls into this category. Finally, *value linkage* is closely related with value acceleration, but it has more to do with the combined effects of an information system rather than the time factor alone. It represents the ripple effect of an improvement in an overall function. In ILIS, savings from the reduction in reporting error and misdiagnosis may be viewed as value linkage. Sensitivity analysis was also conducted to identify key factors and to understand the consequences of changes in key factors and assumptions under various scenarios. Chae et al [6] evaluated the economic performance of the telemedicine system using the IE approach.

Results

System Architecture

The ILIS consists of two modules as seen in Figure 1:

- *Result interpretation module*

  This provides a preliminary diagnosis and quality control (QC) information (e.g. delta check, panic check) using the test results produced by laboratory analyzers and the knowledge of clinical pathologists.

- *Therapy advisor module*

  This provides diagnosis and various therapy advice based on other test results, lifestyle information, and knowledge of family medicine physicians.

Validation of ILIS

In a comparison of diagnoses for 16 disease categories between the actual diagnosis and the diagnosis made by ILIS, diagnoses were the same for 8 diseases; the diagnoses made by ILIS were more accurate than the actual diagnoses in 6 diseases; and less accurate in 2 diseases (Table 1). Nine diseases were correctly predicted by the system in 100% of the cases. Overall predictive rate of ILIS (92.5%) was higher than the actual diagnosis (92.1%).

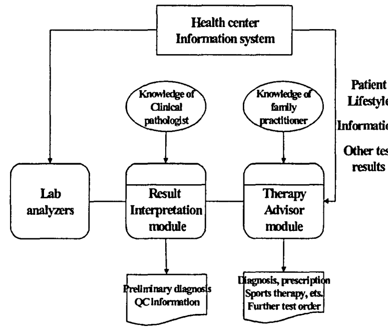

Figure 1 - System overview of the ILIS

Economic Analysis

Cost Benefit Analysis

As seen in Table 2, total costs of ILIS for the health center was $18,200 including software development cost ($10,000), hardware cost ($2,000), medical consultation fee for developing laboratory interpretation and therapy advisor modules ($5,000), and operating cost ($1,200).

Direct benefit was the reduced personnel costs of $4,790 by automating laboratory data processing such as a test order entry (average 3 minutes reduction per test), results interpretation (average 15 minutes reduction per test), diagnosis and prescription (average 3 minutes reduction), and entry of the test results to the system (average 3 minutes reduction).

During the survey period, the average number of screens was 5 tests per day. Direct benefit ($4,790) was obtained by multiplying the reduction of laboratory data procession time per test by the average number of tests per day and personnel costs. A net loss was $13,410 and a benefit to cost (B/C) ratio was 0.26. This shows that a direct (traditional) cost-benefit analysis alone could not justify for the costs of developing and operating ILIS.

However, when the increased revenue from one additional person per day for screening due to the reduction of laboratory data processing time (value acceleration) was added, the cumulative benefit was increased to $31,985 (net benefit=$13,785, B/C ratio=1.75). This was obtained by multiplying the charge for screening ($90.65) by the number of available days for screening per year (300days).

Moreover, when the savings from the reduction in reporting error and misdiagnosis (value linkage) were added, the cumulative benefit was increased to $43,085 (net benefit=$21,660, B/C ratio=2.19. Since most of the reporting errors and misdiagnosis were caused by combined effects of various factors, such as, increasing workload of health workers and clerical errors, they were viewed as value linkage. Without having the actual data, we assumed that 5% of the total number of screenings, which were 1,500 cases per year (5 cases per day x 300 days), had errors from either manual processing of data or misdiagnosis, and that the average medical expenses caused by the misdiagnosis was $100. These assumptions were later varied by the sensitivity analysis. The wage for a laboratory technician, on hourly basis, was $10 and the average time for reprocessing of laboratory data due to such errors was 30 minutes.

Table 1. Comparison of predictive power of diagnosis between the actual and ILIS ( ): percentage

Disease	Cases	Actual	ILIS
Glaucoma	5	5(100)	5(100)
Osteoporosis	7	7(100)	7(100)
Hypertension	58	53(91.4)	54(93.1)
Cystitis	9	8(88.9)	7(77.8)
Hepatitis B carrier	5	5(100)	5(100)
Hepatitis C carrier	2	2(100)	2(100)
Fatty liver	5	5 (100)	5(100)
Alcoholic liver Disease	13	12(92.3)	13(100)
Hyper lipidemia	31	30 (96.8)	30(96.8)
Draft	12	10(83.3)	11(91.7)
Diabetes	9	7(77.8)	8(88.9)
Microcytic anemia	4	3(75.0))	4(100)
Hematochezia	6	6(100)	6(100)
Rheumatoid arthritis	7	6(85.7)	7(100)
No abnormal finding	31	30(96.8)	26(83.9)
Others	23	20 (86.9)	20(86.9)
Total	227	209(92.1)	210(92.5)

Table 2. Summary of costs and benefits

(unit : U.S. $)

			B/C ratio
costs	Software development Cost	10,000	
	Hardware cost	2,000	
	Medical consultation fee	5,000	
	Operating cost	1,200	
	Total costs	18,200	
Benefit	Direct benefit Reduced personnel costs	4,790	0.26
	Value acceleration Increased revenue from one additional person for screening	31,985	1.75
	Value linkage Reduced reporting error Reduced misdiagnosis	39,860	2.19
Net Benefit		21,660	

Sensitivity Analysis

Sensitivity analysis was conducted on a number of additional persons for screening per day (1 ~ 3 persons), different error rates (5 ~ 10%), and different medical expenses ($100 ~ $300) from misdiagnosis. Revenues were steadily increased to $54,390 ($90.65 x 2persons x 300days) and $81,585 ($90.65 x 3persons x 300days) as the number of additional people for screening was increased to two and three, respectively. This resulted in an increase of B/C ratios from 2.19 to 3.68 and 5.18.

Discussion and Conclusion

This paper describes an Intelligent Laboratory Information System (ILIS) that produces diagnosis and therapy advice based on interpreted test results and patient's information. Since there is no clinical pathologist who can interpret laboratory test results in most of the health centers in Korea, the ILIS can help improve the screening process and the outcome of care.

In order to validate the knowledge model, records of 170 patients were collected from practices. In comparison with the final diagnoses, the overall predictive rate of ILIS (92.5%) was higher than the actual diagnoses (92.1%), perhaps due to the fact that ILIS uses patient's lifestyle information in addition to laboratory results. Most of the actual diagnoses were made using only laboratory results by the doctor.

While most expert systems that have been developed in the field of medicine are essentially stand-alone systems, the ILIS is integrated with the health center information system for order entry and patient data entry. Integration with the health center information system has greatly improved the knowledge acquisition, which has been a major impediment to the development of expert systems. In the future, other knowledge models, such as neural network and case-based reasoning, should be used in an ILIS because they can easily acquire knowledge directly from the patient database through such integrated mechanisms. Further, the rules and therapy advice should also be reviewed and refined by a panel of experts in order to be more acceptable to other physicians. At the same time, the system should also be tested in other health centers to assess how acceptable it is to other potential users.

This paper also analyzed the economic feasibility of ILIS to determine whether the benefits of ILIS indeed justify the costs of developing and operating the ILIS. Sensitivity analysis was also performed to identify important factors influencing costs and benefits and to understand how these factors can be changed to improve economic performance of telemedicine. Guyatt et al [7] suggested that sensitivity analysis is an effective tool that deals with uncertainty involved in evaluating intangible benefits, such as the effects on medical expenses resulting from misdiagnosis.

When the ILIS was evaluated based on the traditional cost-benefit analysis, the results showed a heavy net loss with a B/C ratio of 0.26. As several values were added to the analysis based on the IE approach, B/C ratios steadily increased. This shows that expansion of benefits with values can drastically change the entire outcome of the analysis. In addition, the ILIS not only helps screen more people by increasing the capacity of health centers, but also brings in more revenue to the health centers.

In the future, a lifetime electronic health record (LEHR) for community residents should be constructed in order to monitor their health status. Since essential data for medical record are automatically generated by ILIS, it can be easily constructed by developing an interface module between ILIS and LEHR. LEHR can also be used in identifying high-risk groups and evaluating the effectiveness of the previous health services rendered by a health center.

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