An Interrelated Decision-making Model for an Intelligent Decision Support System in Healthcare

NORMADIAH MAHIDDIN1, ZULAIHA ALI OTHMAN, AZURALIZA ABU BAKAR, (Member, IEEE), and NUR ARZUAR ABDUL RAHIM2.
1Center for Artificial Intelligence Technology (CAIT), Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, Bangi 43600, Malaysia
2Regenerative Medicine Cluster, Advanced Medical and Dental Institutes, Universiti Sains Malaysia, 13200, Kepala Batas, Penang, Malaysia

Corresponding author: Normadiah Mahiddin (normadiah@gmail.com).

This work was supported by Universiti Kebangsaan Malaysia (UKM) in part by the Ministry of Higher Education under Grant LRGS/1/2020/UKM-UKM/01/5/2.

ABSTRACT The nature of decision making in healthcare is complex and crucial. It is essential to have a tool that helps with accurate and correct decisions based on real-time data. Moreover, the healthcare process itself is complex, comprising various stages from primary to palliative, closely related to each other, and the process is different depending on the type of disease. Each stage has a crucial decision to be made relying on other stages decisions. Thus, an intelligent decision support system (IDSS) model based on a data mining approach becomes a prominent solution. However, the existing IDSS and Group Decision Support System (GDSS) applied a single-stage approach and primarily focused on development at a certain stage for specific outcomes. In contrast, the nature of healthcare decision-making in each stage is related to the previous stages, which change dynamically. Therefore, this paper proposes an interrelated decision-making model (IDM) for IDSS in healthcare that aims to have an effective decision by utilizing knowledge from previous and following treatment stages known as IDM-IDSS-healthcare. The experiment was conducted using simulated diabetes treatments data that were validated by the medical expert. Eight data sets with distinct sizes were constructed and classified into two types of decision-making categories. Each data set consists of primary and secondary care stages with a range of 25 to 58 attributes and 300-11,000 instances. The experiment results show algorithms J48, Logistic, NaiveBayes Updateable, RandomForest, BayesNet, and AdaBoostM1 obtained the best accuracy in sequence from 46% to 99%. The result also shows the improvement of decision-making efficiency with the prediction model accuracy has increased up to 56%. In addition, all respondents agreed in a focus-group discussion with medical and information technology (IT) experts that the proposed IDM-IDSS-healthcare is practical as a healthcare solution. Moreover, the solution for the development of IDM-IDSS-healthcare should use the multi-agent approach.

INDEX TERMS Healthcare, Diabetes, Data Mining, IDSS, IDM.

I. INTRODUCTION
A comprehensive healthcare system is one of the benchmarks of a nation’s development. Meanwhile, correct and effective decision making is one of the key components of the healthcare system [1], [2]. Decision making in healthcare has long been recognized as difficult and complicated, due to the complexity of the healthcare sector itself [3], [4]. The reason for its complexity is that it consists of many closely interlinked elements with specific boundaries that involve multiple stages [5]. These elements refer to the stages of healthcare, clinical data, patient data, etc. The term ‘stage’ here was referred to the level of healthcare such as primary care, secondary care, tertiary care etc.

Rapid evolution has been occurring in healthcare for a long time. This evolutionary development has transformed healthcare’s previous structure, from horizontal to recursive and iterative, with a total of five stages of care [6]-[8]. Even though decision support system (DSS) technology has been used since the late 1950s to support healthcare decision making, it has continued to evolve in
conjunction with the rapid evolution of healthcare [9]. However, to date, the development of the DSS has only focused on data management and knowledge in certain stages of healthcare [10],[11]. This means today's DSS development is mostly in single-stage approach where data flow occurs only at one stage or is a single solution in nature.

In this study, the term ‘single-stage’ refers to situations in which data flows at one stage or from several stages, with one or more decision making at one particular stage only and does not take into account the everchanging state of the data from other stages. This situation means that today's healthcare decision-making process is not based on the overall context of the respective healthcare stage. In contrast, a decision in healthcare should consider the interconnectedness between each healthcare stage holistically [12]. The lack of holistic DSS development for healthcare has an inevitable impact on the accuracy of results [13]. Holistic decision making in healthcare allows observation and evaluation of the entire situation to produce more accurate results than the previous approach.

As a result, research is needed on a decision-making flow model in healthcare based on the stages of care, with this model able to be used as a foundation for DSS development in general. The realities of the best decision-making process in healthcare require the sharing of information among key decision-makers. Despite the existence of the group decision support system (GDSS) which allows many decision-makers to be involved in decision making, the architecture and analysis of the data obtained are still independent because the GDSS architecture is independent. Even though the GDSS has now been improved with intelligent techniques such as data mining, to date, it remains a single-stage or single solution [14], [15].

The use of information and communications technology (ICT) now allows access to medical information from one setting to another, thus facilitating the sharing of medical information. The use of various technological devices in healthcare helps physicians with more and more diagnoses. However, none of these technologies can currently handle the overall flow of information in the healthcare sector, amid the various technological advances currently available in this sector. Thus, another important factor here is how to use the knowledge generated from this information [16]. This study asserts that DSS development in healthcare must be based on a holistic decision-making model in healthcare to tackle these limitations.

As a result, the key contributions of this study are summarized as follows:

1. An interrelated decision-making model for an intelligent decision support system in healthcare, known as IDM-IDSS-healthcare, is proposed, with this model to be used to obtain accurate decision making in the field of healthcare.

2. A unique feature of IDM-IDSS-healthcare is a decision-making flow model that can include the interrelated relationships between each stage of care in healthcare.

3. IDM-IDSS-healthcare consists of:
   (i) healthcare stages based on the area of the problem,
   (ii) decision flow occurring between healthcare stages,
   (iii) data attributes for the respective healthcare stages, and
   (iv) the amount of data flowing and not flowing from a respective healthcare stage to another respective healthcare stage and vice versa. The precision of decision making was found to be influenced by large volumes of data. All contents of IDM-IDSS-healthcare will be analyzed, operated, and used to make effective decisions in the respective healthcare stages.

The remainder of this paper is structured as follows. Section II presents an overview of the healthcare system as well as a review of DSS in healthcare. Section III presents the methodology applied in this research and the details of the proposed decision-making model. Section IV presents the experiments and Section V presents the results. Finally, Section VI presents conclusions about the proposed decision-making model as well as future research directions.

II. RELATED WORK

Various efforts have been done toward having an effective healthcare management system. However, one of the most important factors in determining one’s quality of life is access to high-quality health care [17], [18]. As a result, the goal of the entire field of healthcare is to improve the health of the population as a whole [19]. Taylor, et. al. (2003) stated that a healthcare system is defined as a system that consists of interconnected elements and stages [20]. On the other hand, Kovacic, et. al. (2008) defines a healthcare system in more holistic as it is not just limited to healthcare organization but includes political, economic and cultural, technical and organizational factors, relationships, processes and elements, in which individuals, groups and communities are interconnected, have a goal to meet their health needs [21].

The health care system, in general, is made up of three interconnected components: (1) healthcare service consumer groups, (2) healthcare provider groups such as doctors, and (3) organizations that manage healthcare services [22], [23]. However, the focus of this work is on decision making in healthcare according to the structure of the healthcare system and the interrelationships between the stages of healthcare itself. Only a few prior studies in the literature have explored the stages of healthcare, with few researchers having conducted work on these stages. Literature reviews have indicated that healthcare stages are traditionally shown horizontally, with only a sequential relationship between these stages [24], [25]. With the passing of time, the stages of healthcare services have also changed. Today, the stages of healthcare have undergone a transformation from a sequence in linear form to a cycle that can be iterative.

Besides, currently, healthcare has progressed from the traditional one stage to the current five stages. According to the standard practice of the Health Care Services System, the stages of health care consist of five stages of care, (1) Primary Care (PC) is a basic health care service to identify early symptoms, (2) Secondary Care (SC), has been identified as diseased but focus on identifying disease in the early stages, (3) Tertiary Care (TC), contains treatment to reduce the effects of the disease,
Quaternary Care (QC), contains treatment with a very high medical level and (5) Palliative Care (Pal-C), supportive care services for patients with the disease seriously [26]-[28]. These five stages of care are interrelated with each other. In medical, most stages of care have a sequential relationship with the term ‘refer to’ and have a returned relationship with the term ‘continue follow-up’ among these stages. Thus, the interrelationship among these five stages of healthcare was identified as recursive and iterative [29], [30].

A. DECISION SUPPORT SYSTEM IN HEALTHCARE
The results of the literature review showed that different decisions produced different risk stages [31]. This highlights the need to identify a decision-making process that takes the healthcare stage into account to make accurate decisions in the healthcare sector. It is recognizable from the differences in these risk stages that they form the basis for the healthcare system’s division into several stages of care. Thus, the focus of this study is on the complex theory of healthcare based on the decision-making aspects in various stages of healthcare. Previously, computer experts have investigated and manufactured DSSs to help people make better choices in different aspects of their lives.

Thus, based on Figure 1, we can see the evolution of DSS began with Personal DSS, which emerged from the evolution of technologies that began with computer-based information systems, operations research or management science, and behavioural decision theory [32]. Following the existence of Artificial Intelligence (AI) and the development of Social Psychology, DSS evolved into IDSS and GDSS. During this period, the first DSS for healthcare, MYCIN, was developed in 1975, followed by INTERNIST-I (1982) and DXplain (1987) [33]-[35]. Since then, DSS in healthcare has evolved in tandem with technological advancements.

These developments have led to the existence of a Group Decision Support system (GDSS), Executive Information System (EIS) and Intelligent Decision Support System (IDSS). As far as GDSS technology is concerned, even though a GDSS includes multiple decision-makers and has been enhanced with smart techniques, the GDSS design and data analysis still comprise a single solution. The same applies to EIS and IDSS. Technology is constantly evolving. IDSS has evolved into knowledge management-based IDSS, interactive and integrated IDSS, and natural language-based IDSS. Meanwhile, EIS and NSS evolved into analytics-based IDSS and cloud-based IDSS [36].

Further, the usage of DSSs in the healthcare sector is growing and increasing rapidly in line with the rapid evolution of the healthcare sector itself. The computer-based Healthcare Information Management System, also known as the Electronic Health Record System, is broadly classified into three types: administrative information management system, clinical information management system, and financial information management system [37]-[39]. This study, however, only looks at the Clinical Decision Support System (CDSS), which is a subcategory of the clinical information management systems. DSS has evolved till recently, with all technologies attempting to be incorporated, resulting in Multiagent-based IDSS. The same applies to CDSS. Then, CDSS has evolved to Intelligent CDSS (ICDSS) until recently to Multiagent ICDSS [40], [41].

However, the use of ICDSS technologies nowadays were still rising as shown in Table 1. Table 1 showed, the first aspect is whether the source of the data analysis for the DSS in healthcare is obtained from different stages of care. The second aspect is whether the decision model of each DSS in Table I is dynamic. The third aspect is whether the DSS in Table I applies artificial intelligence (AI) techniques, while the fourth aspect considers the DSS from the perspective of the type of intelligence techniques used. For the first aspect, the analysis results found that none of the DSSs in Table I originated from more than one healthcare stage. This shows that these DSSs have all been developed specifically for only certain stages of care within the healthcare sector. Therefore, most existing DSSs have been developed separately based on a specific healthcare stage.

As shown in Table 1, 10 studies have examined a DSS developed for the primary healthcare stage as follows: FNDSB [42]; DSS with FES [43]; PsyDis [44]; EMBALANCE [45]; DSS with hybrid triage [46]; CDSS recommendation for guidance [47]; CDSS for early detection of SIRS [48]; IDS for Parkinson's disease [49]; DSS for antibiotic prescription [50]; DSS for smart homes for dementia [51]; Hybrid rough set reasoning model (H2RM) [52]; Smart healthcare monitoring system [53],[54]; and the Multi-criterion decision support system (MCDSS) [55]. The remainder of
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3160725, IEEE Access

**TABLE 1. IDSS based on Stages of Healthcare.**

| IDSS name                                                                 | Q1 | Q2 | Q3    | Q4                                                                 |
|---------------------------------------------------------------------------|----|----|-------|----------------------------------------------------------------------|
| Fuzzy-neuro decision support system for back pain diagnosis (FNDSBS)[42]  | No | No | Yes   | Data mining                                                          |
| CODES [22]                                                                | No | No | Yes   | Data mining                                                          |
| HeartMan [59]                                                             | No | No | No    | Sensor                                                               |
| DSS with fuzzy expert system (FES)[43]                                     | No | No | Yes   | Fuzzy expert system (FES)[43]                                        |
| PsyDis [44]                                                               | No | No | Yes   | Ontology and logical conclusion mechanisms                          |
| EMBALANCE [45]                                                            | No | No | Yes   | Data mining                                                          |
| CDSS for diabetic retinopathy [65]                                        | No | No | Yes   | Data mining                                                          |
| ADDIS [58]                                                                | No | No | Yes   | Consolidation of data models                                        |
| DSS for operating room scheduling at Spanish hospital [66]                | No | No | Yes   | Optimization procedure                                              |
| DSS hybrid triage [46]                                                    | No | No | Yes   | A hybrid approach using rule-based reasoning and fuzzy logic         |
| DSS for individual radiation oncology and participation [67]              | No | No | Yes   | Data mining                                                          |
| SKION (Children's Oncology Foundation Netherlands/Stichting Kinder-oncologie Nederland [47] | No | No | Yes   | Combination of loud thinking methods and suggestion analysis         |
| IDSS for cases in pathological test orders [68]                          | No | No | Yes   | Data mining and text mining                                         |
| CDSS for diagnosis of heart disease [69]                                  | No | No | Yes   | Hybrid approach with a combination of fuzzy inference and fuzzy analytic hierarchy process |
| ICDSS for opioid management [70]                                          | No | No | Yes   | Rule-based workflow focus strategy method                            |
| DSS smart medicine [71]                                                   | No | No | Yes   | Enhanced hierarchical clustering and random decision forest          |
| CDSS for early detection of system inflammation response syndrome (SIRS) [48] | No | No | No    | Based on open electronic health record                               |
| Intelligent diagnostic system (IDS) for Parkinson's disease [49]         | No | No | Yes   | Optimization of chaotic bacterial foraging – enhanced fuzzy k-nearest neighbor [FKNN] (CBFO-FKNN) approach [49] |
| DSS for antibiotic prescription [50]                                      | No | No | No    | Statistical analysis                                                 |
| COLLA-BORADI [72]                                                        | No | No | Yes   | Rule-based method                                                    |
| Intelligent system for anticipating intradialytic hypotension in chronic hemodialysis [73] | No | No | Yes   | Data mining                                                          |
| DSS through smart homes for dementia [63]                                  | No | No | Yes   | Data mining                                                          |
| Hybrid rough set reasoning model (H2RM) [64]                              | No | No | Yes   | Data mining – Hybrid rough set                                       |
| Smart healthcare monitoring system [65],[66]                               | No | No | Yes   | Data mining – Ensemble deep learning and feature fusion              |
| Early warning system [67]                                                 | No | No | Yes   | Data mining and machine learning                                     |
| Multi-criterion decision support system (MCDSS) [68]                      | No | No | Yes   | Multi-criterion decision support                                     |

**Note:** Q1 = “Sources of data for analysis from various stages of healthcare?”, Q2 = “The decision model is dynamic?”, Q3 = “Applied artificial intelligence technique?”, Q4 = “Name of artificial intelligence technique applied”.

The DSSs in Table 1 have been developed for secondary care, except for the Intelligent system for anticipating intradialytic hypotension in chronic hemodialysis [56] and the Early warning system [57] which was developed for tertiary care.

Therefore, the data collected for analysis in the DSS for each of these studies were only from one stage, with that stage being independent, with no relationship to either the next stage or the previous stage of healthcare. In reality, decision making in the healthcare system is interrelated at every stage. Therefore, to improve the quality of decision making, research into the development of the DSS must take into account the interrelationships between the different stages of healthcare. In terms of the second aspect, as shown in Table 1, most of the existing DSSs have a static decision-making model, with none using a dynamic decision-making model. For example, H2RM is a DSS that uses patient charts and online guidelines to generate a decision model once in the system.

Aside from that, most DSSs showed in Table 1 use a variety of data sources, such as the ADDIS data model, which was created through the assisted extraction of trial registries, manual extraction of abstract databases, text mining in industrial databases, and extraction of ontology-based eXtensible (OBX) and ontology of clinical research (OCR) mapping rules [58]. Apart from ADDIS and H2RM, existing DSSs with a static decision-making model include the Smart healthcare monitoring system, Early warning system, and MCDSS for COVID-19.

Even though these data models are built from various data sources, the generation of the decision model occurs at one time only. This again confirms that a dynamic decision-making model is needed to improve the effective of decision making. Through a dynamic decision-making model, the DSS will always have the...
latest decision model from which to generate decision support. The third aspect is whether the DSS applies artificial intelligence (AI) techniques. As shown in Table I, almost all existing DSSs use AI techniques, except for the DSS called HeartMan and the DSS for the early detection of system inflammation response syndrome (SIRS) [48],[59]. The AI techniques are now essential for producing accurate predictive models for effective decision-making models in DSSs.

Furthermore, the AI methods used are diverse. The fourth aspect concerns the type of AI techniques used, with data mining currently one of the most popular techniques used in the existing DSSs, as shown in Table I. The process of data mining is interactive and iterative. The data mining approach can also be used to identify important data attributes that have a high influence on the process of obtaining accurate results. Furthermore, the data mining approach can be used to identify critical data attributes that have a high influence on the process of obtaining accurate results [60]-[62]. Consequently, the form and status of the data collected for the data mining process are vital. Therefore, data mining research is required. The findings are considered in the data mining process to ensure quality results by using data mining methodology. [63],[64],[76].

B. ISSUES AND CHALLENGES IN A COMPLETE HEALTHCARE DECISION SUPPORT SYSTEM

Various methods are used to produce high-quality DSSs for healthcare. Still, data mining is widely used in the development of DSS research. It shows that the data mining method used in various types of DSS has proved effective in improving the accuracy of results [52],[53],[55]. Despite the significant achievements and success of IDSSs, acceptance and use of many types of DSS in healthcare have not yet been widely achieved [74]. The ineffective use of ICDSS is one of the identified problems. This issue arises due to several factors, including a lack of understanding of the ICDSS workflow's consequences. Furthermore, DSS health researchers argue that systems need to be studied to regulate complex workflows [10]. In addition, DSS health researchers argue that systems need to be developed to regulate complex workflows [75].

According to the findings of prior ICDSS observations, as set out in Table 1, ICDSS development is mostly based on specific stages of healthcare. The lack of development of decision-making support systems for overall healthcare affects the quality and effectiveness of decision making. Comprehensive decision making allows all aspects to be observed and assessed. This situation produces more accurate results than options considering only one stage or one aspect. It is required to explore a decision-making model based on all healthcare stages to use as the cornerstone for the development of ICDSS. [48], [67], [70].

Figure 2 illustrates the current form of ICDSS data flow and a single decision-making concept in most of the current existing ICDSS architecture. Despite the fact that certain studies take into consideration the flow of data from multiple sources, however, the decision-making is still performed once and at a specific stage of healthcare only [78],[79].

.. Image: FIGURE 2. Data flows in most of the current existing ICDSS architecture in a stage.

.. Image: FIGURE 3. Data flows in GDSS architecture in a stage.
III. METHODOLOGY

Figure 5 shows the research methodologies for this study that consists of three stages: formulate IDM-IDSS model for healthcare, experiment, and evaluation. This research applies a mix-method qualitative, quantitative, and experiment. There is an extensive literature review, analysis of healthcare documents used locally and internationally, and past research on healthcare decision-making scenarios to formulate the IDM_IDSS model. The model consists of flow modelling with a mathematical formulation. The literature review focuses on various types such as DSS, IDSS, GDSS, CDSS, ICDSS, healthcare, healthcare systems, and multi-agent systems (MAS), as stated in related work.

While, the Healthcare Document Analysis involved the Malaysian Clinical Practice Guideline (CPG) on Diabetes Management, CPG on Diabetic Nephropathy Management, CPG on Chronic Kidney Disease Management, Pre-House Officer (HO) Crash Course documents, Quick References for Professional Examination of Internal Medicine, National Renal Data Set, the hemodialysis treatment form, and some examples of blood test reports. While the Analysis Healthcare Decision Making Scenarios uses the three past research papers [25],[26],[29].

Two dedicated doctors from Advanced Medical and Dental Institutes (AMDI), University Science Malaysia (USM), are involved in the model formulation processes. One is the diabetes specialist doctor, and the second is the children specialist doctor, the Head of Regenerative Medicine Cluster, who advised and validated the proposed model. They also validated that the Diabetes IDM model includes the data preparation. The Diabetes IDM model covers the five stages of iterative decision-making. However, the experiment only focuses on preparing the data set for...
diabetic primary care and secondary care stages only. The data sets have two types of decision-making: diagnosis on a diabetic level and stage of care, either remain at the current stage, previous stage, or next stage.

Hence, eight data sets are prepared. Each data set consists of two data as a primary care and secondary care stage but has four different sizes of instances and attributes, ending up with 192 experiments as each data set is experimented with using six machine learning algorithms. The performance of IDM is evaluated based on the changes in accuracy prediction models towards the size. Lastly, the proposed IDM Model for Healthcare, the Diabetes IDM model, and the experiment results are shown to twelve doctor practitioners for quantitative feedback evaluation using a focus group discussion method.

A. AN INTERRELATED DECISION-MAKING MODEL FOR IDSS IN HEALTHCARE

The model, IDM-IDSS-healthcare, is characterized as a set of elements (stages) that require decision making following the type of disease and stage supported by the healthcare organization or centre. ABC Hospital (a pseudonym) has, for example, only assisted the management of heart disease from Stages 1 to 3. Meanwhile, Stage 4 management should be applied at Hospital DEF (also a pseudonym). The model, IDM-IDSS-healthcare, thus comprises an IDSS collection consisting of care and data flow stages for each intelligent decision support system (IDSS). The treatment stage is indicated by P, while the data flow between care levels, represented by A, consists of outflow and data entry. The IDM-IDSS-healthcare definition is presented in detail below:

\[ IDM-IDSS-healthcare = \{DSS_1, DSS_2, DSS_3, \ldots DSS_n\}, \]  

in which DSSi, i=1,2,3, ... n consists of P and A,

where IDSS = \{P,A\} …

where

\[ P = \text{stage of care and} \]

\[ A = \text{data flow}. \]

The IDM-IDSS-healthcare set consists of several stages depending on the area or organization of the problem. Thus, in summary, the \( P \) element in the IDM-IDSS-healthcare set can be represented by the following equation:

\[ IDM - IDSS - Healthcare = \{P_i\}_{i=1}^n \]  

Table 2 below shows the IDM-IDSS-healthcare representative list.

| Representative | Definition            |
|---------------|----------------------|
| \( P \)       | Stages of healthcare |
| \( A \)       | Flow that occurs between the levels of care |
| \( PK \)      | Decision Maker       |
| \( M \)       | Goal                 |

The stages of care \( P \) comprise the following components:

\[ P = \{\text{Decision Maker}, \text{Goal}, \text{Task}, \text{Data}\} \]

Therefore, \( P \) can be represented by representatives as follows:

\[ P = \{PK, M, T, D\}, \]  

(3)

Table 3 then describes the elements in \( P \) and presents their definitions.

| Subcomponent | Definition                                      |
|--------------|------------------------------------------------|
| \( PK \)     | People who have the right to use the system    |
| \( M \)      | A goal or something to accomplish on a task at a certain level |
| \( T \)      | Activities are undertaken to achieve the goal  |
| \( D \)      | Record with a list of components and data attributes at the care level |

The element ‘data’ \( D \) comprises the following elements based on Table 4:

\[ D = \{kp_i, r_i\}_{i=1}^n \]  

(4)

| \( kp_1 \) | \( kp_2 \) | \( kp_n \) |
|------------|------------|------------|
| \( a_1 \)  | \( a_2 \)  | \( a_n \)  |
| \( a_{r_1} \) | \( a_{r_2} \) | \( a_{r_n} \) |
| \( a_{r_1} \) | \( a_{r_2} \) | \( a_{r_{k_1}} \) |
| \( a_{r_2} \) | \( a_{r_3} \) | \( a_{r_{k_2}} \) |
| \( a_{r_3} \) | \( a_{r_4} \) | \( a_{r_{k_3}} \) |
| \( \ldots \) | \( \ldots \) | \( \ldots \) |
| \( a_{r_n} \) | \( a_{r_{k_n}} \) | \( a_{r_n} \) |

Meanwhile, components \( kp \) is composed of several attribute elements \( a \) with the last component, \( kpn = ks \), as follows.

\[ kp = \{a_i\}_{i=1}^n \]  

(5)
In addition, Figure 7 shows the general IDM-IDSS-healthcare model with the maximum number of care stages (n = 3). Based on Figure 5, flow K is always going to a higher stage, while flow S is always going to be lower than the current stage. Meanwhile, the flow R is always at the same level. In addition, the flow K was not only sequentially increased but also increased by more than one level. At the same time, S-flows may occur sequentially with lowering stages or may occur with a decrease of more than one level at a time. Following are the steps for the development of IDM-IDSS-healthcare:

1) Identify the stages involved and the maximum number of stages involved. The identification needs to be carried out by the field specialist at this point.
2) Identify the flow between the different stages involved. At this point, the identification needs to be carried out with the approval of the specialist in the field.
3) Identify the data attributes list for each stage. Again, identification must be done with the approval of a specialist in the field at this point.
4) Calculate the amount of data flowing and not flowing, based on the list of data attributes and the number of data record assumptions, to obtain an overview of the data flow between each of the stages involved.
5) Develop a complete IDM-IDSS-healthcare model with data flow and the number of attributes flowing between each of the stages involved.

In the IDM-IDSS-healthcare model, the maximum number of care levels is three (n = 3). Based on Figure 5, flow K is always going to a higher stage, while flow S is always going to be lower than the current stage. Meanwhile, the flow R is always at the same level. In addition, the flow K was not only sequentially increased but also increased by more than one level. At the same time, S-flows may occur sequentially with lowering stages or may occur with a decrease of more than one level at a time.

The following steps are taken for the development of IDM-IDSS-healthcare:

1. Identify the stages involved and the maximum number of stages involved. The identification needs to be carried out by the field specialist at this point.
2. Identify the flow between the different stages involved. At this point, the identification needs to be carried out with the approval of the specialist in the field.
3. Identify the data attributes list for each stage. Again, identification must be done with the approval of a specialist in the field at this point.
4. Calculate the amount of data flowing and not flowing, based on the list of data attributes and the number of data record assumptions, to obtain an overview of the data flow between each of the stages involved.
5. Develop a complete IDM-IDSS-healthcare model with data flow and the number of attributes flowing between each of the stages involved.
B. An Interrelated Decision-Making Model for Diabetes

The data flow value of IDM-IDSS-healthcare for the diabetes case study shows that the concept of IDM-IDSS-healthcare has been able to deliver significantly better results. Based on the principles of data mining, more information will produce more accurate results. The concept of IDM-IDSS-healthcare forecasting can therefore help in the process of producing more accurate decision making. Decision making in healthcare by its nature is very interlinked between stages. Preserving information on treatment and moving among the stages leads to accurate healthcare decision making. This situation follows the basic principle of data mining in that the more data, the more accurate the decision-making process.

Therefore, this section describes the results of the development of IDM-IDSS-healthcare for the diabetes case study. The result showed how well IDM-IDSS-healthcare could be used to increase the accuracy of healthcare decision making. Following are the steps in the development of the IDM-IDSS-healthcare case study on diabetes:

- Identify the stages
  The first step is to identify the stages of healthcare and the maximum number of stages of healthcare involved in diabetes. In the case of diabetes, this may involve all stages of healthcare. The maximum number of medical stages for the diabetes case study is therefore five. Subsequent stages of healthcare were identified as primary, secondary, tertiary, quaternary, and palliative.

- Identify the flow between each level
  Existing streams between each level are identified, following the identification of the existing levels of care for cases of diabetes. The identification of these emerging streams between the different levels is integrated after the information has been collected through interviews and discussions with healthcare professionals on diabetes diagnosis and the determination of healthcare levels. Figure 6 shows the data streams identified that are either at a specific stage of care or between one stage of care and another stage of care. These data streams are represented as a, b, c, d, e, f, g, h, i, j, k, l, m, n, and o, as shown in Figure 6.

- Identify the list of data attributes
  A list of data attributes for each stage of care was collected after identifying the current stages of healthcare and trends for the diabetes case study. Next, the list of data attributes was evaluated and validated by healthcare professionals through interviews and discussions.

- Calculate the total data
  This step calculates the sum of the data that flow and the sum of the data that do not flow. The calculation is made based on the number of data records at each level of healthcare involved. The example of total data records for each stage of healthcare in the diabetes case study is shown in Table 7 and Table 8. The amount of data is based on the list of data attributes for each stage of healthcare (primary, secondary, tertiary, quaternary, and palliative) and the list of data attributes involved in the data flow between the stages of healthcare

- Complete the development of IDM-IDSS-healthcare for diabetes

The final step in the development of IDM-IDSS-healthcare is now discussed with its use in the diabetes case study producing the data flow results illustrated in Figure 8 and Figure 9 which shows the IDM-IDSS-healthcare data flow values. The values, assuming that all stages of care are provided, are derived from approximately 300 treatment records. Further, in order to support the evaluation in this study, focus groups discussion (FGD) were chosen as one of the approaches under the formative evaluation approach, which is one of the CDSS evaluation categories [79].

IV. Experiment

The evaluation was carried out to demonstrate the effectiveness of the proposed IDM-IDSS-healthcare, therefore the data preparation is the crucial part. The source of data used in the experiment was based on data from the diabetes case study as illustrated in Figure 8 and Figure 9. However, because of the constraints to obtain complete real data, the data for this experiment were generated simulation data based on analysis documents healthcare and analysis decision making past researches.

A. Data Set

As stated in methodology, each stage has two types of decision making: diagnosis diabetes level and predict the stage of care to go. The data sets only prepared data set at primary and secondary stage only. Furthermore, each data set is divided into two types of data changing the size of the data set: a data set with a relationship with R only and a data set with relationships between R, K, and S (refer to Figure 6).

The first type of data set consists of all data but only at one healthcare stage either at primary or secondary only. This type of data set has four different sizes of instances which is 300, 600, 2000 and 5000 for both diabetes diagnosis and predict the stage of care as shown in Table 7 and Table 8. Table 8 shows the second type of data set which have an R, K and S relationship. It involves a combination of data between stages which is data from previous and following treatment stages. Four different sizes of data sets have been prepared for this research. The number of attributes and instances were different based on the stage of care.

Therefore, a total of eight data sets have been prepared with each data sets has data of primary care and secondary care stage. The first type of data sets for primary care stage were (300,41), (600,41), (2000,41) and (5000,41). Next, the second type of data sets for primary care stage were (1200,57),
FIGURE 8. IDM-IDSS-healthcare with data flow values for diagnosis class in a diabetes case study.

FIGURE 9. IDM-IDSS-healthcare with data flows values for the stage of care class in a diabetes case study.
TABLE 6. Number of Attributes Per Stage of Healthcare.

| Stages of healthcare | Number of attributes (as) | Amount of data in the care stage (assuming the number of data records, r = 300) |
|----------------------|--------------------------|--------------------------------------------------------------------------------|
| L = 1                | a = 41                   | 12,300                                                                         |
| L = 2                | a = 42                   | 7,500                                                                          |
| L = 3                | a = 67                   | 20,100                                                                         |
| L = 4                | a = 31                   | 9,300                                                                          |
| L = 5                | a = 57                   | 17,100                                                                         |

(2400,57), (8000,57) and (11000,57). Meanwhile the first type of data sets for secondary care stage was (300,25), (600,25), (2000,25) and (2000,25) and (5000,25). Lastly, the second type of data set for the secondary care stage was (1200,36), (2400,36), (8000,36) and (11000,36). Next, Table 6 showed the number of attributes for each stage of care in the diabetes case study with data records assumption is equal to 300.

B. EXPERIMENT SETTING

The experimental conducted for each data set using WEKA (version 3.8) data mining tool. The WEKA was applied because the IDM-IDSS-healthcare will be implemented based on multi-agent development in the Java Agent Development Framework (JADE) environment in future. The JADE environment will be applied later to become future multi-agent ICDSs in healthcare. The experiments were conducted using CPU intel 334Mhz with memory 16 Mb RAM.

Table 7 and Table 8 show that for the two categories of diagnosis class and stage of care class as 8 data sets. Each data set has primary and secondary care data. Therefore, the experiment conducted 16 sets of data using six types of algorithms to obtain the accuracy model at primary and secondary stages which end with 192 experiments times. The six algorithms are J48, Logistic, NaiveBayes Updateable, RandomTree, BayesNet and AdaBoostM1. The experiment uses a 10-cross validation method and selects the best accuracy for each data set. Figure 8 and Figure 9 show a recursive flow of data from one stage to another in the case of the R-relationship (see Figure 6). Figure 8 shows a recursive flow of data for prediction on diagnosis model while Figure 9 shows a recursive flow of data for prediction on the stage of care model.

The R-relationship is a common relationship within existing decision support systems (DSSs). The K-relationship, on the other hand, indicates the data flow from one stage of healthcare to another. Meanwhile, relationship S shows the flow of incoming data from one healthcare stage to another. In the current DSSs, the relationship between K and S does not consider. Therefore, this study has proposed the IDM-IDSS-healthcare model in order to enable the K–S relationship in today’s decision support system (DSS). Thus, the DSS can produce more accurate results with both K- and S-relationships. This situation is consistent with the principle of data mining, which indicates that when more information is provided, more knowledge is generated, and decision making is more accurate.

V. RESULT

The findings showed IDM-IDSS-healthcare was workable and improved the decision-making accuracy. This was supported by the findings of expert evaluation via the focus group method. Thus, the following section discussed detail the experiment results in section A and evaluation expert in section B.

A. EXPERIMENT RESULT

Even though during experiments has collected various types of measurement. However, Table 7 and Table 8 only shows the accuracy result for each experiment to show the impact of accuracy for the proposed interrelated decision-making. The table shows the accuracy of eight data sets for primary and secondary stages for both diabetes diagnosis and stage of care decision. The table shows that algorithm J48 consistently shows as the best model for all data sets experiment includes both data sets for diabetes diagnosis and stage of care with accuracy from 99.3% to 100% as marked with bold. The table also shows the second-best algorithm is Logistic, followed by NaiveBayes, Random Tree, BayesNet, and AdaBoostM1. On the other hand, the AdaBoostM1 algorithm shows the lowest average percentage accuracy as marked as italic, with accuracy between 46.8% to 92%. The algorithm is less stable compared to other algorithms.

Then, based on symbol representations shown in Table 9, Figure 10 and Figure 11 clearly show the accuracy result of each algorithm for both types of decision-making models, respectively, that support the previous statement. All figures show accuracy increment by adding new instances and the number of attributes. However, there was a minor increment when adding the number of attributes. Both figures consist of 4 sub-figures as a) to d). Figure a) and c) show comparative accuracy results of each algorithm for primary and secondary stages, respectively. The number of instances increases at the same stages without adding new data from other stages known as R-Relationship. While figures b) and d) show the comparative result of each algorithm for the primary care and secondary care, respectively, in which the number of instances and the number of attributes are increased because having new data obtained from other stages, known as R-, K- and S-relationships.

Figures a) and b) in Figures 10 and 11 show the accuracy increase while the number of instances increases. The figures show the most drastic accuracy changes in AdaBoostM1 compared to other algorithms. Since the J48 has obtained high accuracy, the accuracy does not see an increase in parallel with an additional number of instances. Based on both figures, Table 10 shows the accuracy increment ratio for both types of relationships. The table shows BayesNet shows the highest accuracy increment ratio, follow by AdaBoost, NaiveBayes, Random Tree, Logistic, and lastly, J48. It can be concluded
### TABLE 7. Comparison of Data Accuracy Results by Different Types of Algorithms for R-Relationship.

| Class       | Type of Algorithm | Data Set 1                  | Data Set 2                  |
|-------------|-------------------|-----------------------------|-----------------------------|
|             |                   | Primary Care | Secondary Care | Primary Care | Secondary Care | Primary Care | Secondary Care |
|             |                   | (Records, Attributes) | (Records, Attributes) | (Records, Attributes) | (Records, Attributes) | (Records, Attributes) | (Records, Attributes) |
| Diagnosis   | BayesNet          | 75.1          | 85.1           | 74.1          | 89.3          | 85.8          | 95.1          | 88.1          | 96.1          |
|             | NaiveBayes Updateable | 90.0         | 95.7           | 90.0          | 95.7          | 91.0          | 96.8          | 91.2          | 96.8          |
|             | Logistic          | 96.0          | 98.0           | 97.1          | 99.9          | 98.1          | 99.5          | 98.2          | 99.7          |
|             | AdaBoostM1        | 66.8          | 84.3           | 66.9          | 92.0          | 61.1          | 85.3          | 61.1          | 86.1          |
|             | J48               | 99.6          | 99.9           | 99.7          | 99.9          | 99.7          | 100           | 99.8          | 100           |
| RandomTree  | 90.7              | 99.0          | 91.0           | 99.0          | 91.0          | 99.0          | 92.0          | 99.0          | 99.0          |

### TABLE 8. Comparison of Data Accuracy Results by Different Types of Algorithms for R-, K-RESULTS BY DIFFERENT TYPES OF ALGORITHMS for R-, K- AND s-RELATIONSHIPS.

| Class       | Type of Algorithm | Data Set 1 | Data Set 2 |
|-------------|-------------------|------------|------------|
|             |                   | Primary Care | Secondary Care | Primary Care | Secondary Care | Primary Care | Secondary Care |
|             |                   | (Records, Attributes) | (Records, Attributes) | (Records, Attributes) | (Records, Attributes) | (Records, Attributes) | (Records, Attributes) |
| Diagnosis   | BayesNet          | 70.1        | 81.1        | 70.1        | 89.3        | 75.8        | 90.1        | 78.1        | 93.1        |
|             | NaiveBayes Updateable | 90.0       | 95.7       | 90.0       | 95.7       | 91.0       | 96.8       | 91.2       | 96.8       |
|             | Logistic          | 96.0        | 98.0        | 97.0        | 99.9        | 98.1        | 99.5        | 98.2        | 99.7        |
|             | AdaBoostM1        | 46.8        | 64.3        | 46.9        | 82.0        | 51.1        | 65.3        | 51.1        | 66.1        |
|             | J48               | 99.3        | 99.7        | 99.3        | 99.7        | 99.7        | 100         | 99.8        | 100         |
| RandomTree  | 88.7              | 98.7        | 88.8        | 98.7        | 91.3        | 98.8        | 92.0        | 98.9        | 98.9        |

### TABLE 9. Symbol Representation for the Types of Algorithms.

| Symbol Representation | Name of Algorithm | Symbol Representation | Name of Algorithm |
|-----------------------|-------------------|-----------------------|-------------------|
| a                     | BayesNet          | b                     | NaiveBayes Updateable |
| c                     | Logistic          | d                     | AdaBoostM1        |
| e                     | J48               | f                     | RandomTree        |
FIGURE 10(a). Primary care stage with different instances for diagnosis class.

FIGURE 10(b). Primary care stage with different attributes and instances for diagnosis class.

FIGURE 10(c). Secondary care stage with different instances for diagnosis class.

FIGURE 10(d). Secondary care stage with different attributes and instances for diagnosis class.

FIGURE 11(a). Primary care stage with different instances for the stage of care class.

FIGURE 11(b). Primary care stage with different attributes and instances for the stage of care class.

FIGURE 11(c). Secondary care stage with different instances for the stage of care class.

FIGURE 11(d). Secondary care stage with different attributes and instances for the stage of care class.
that increasing the instances has increased the accuracy except for J48. It is because the J48 has obtained high accuracy, and additional instances do not change the accuracy. Furthermore, the table also shows that most of the accuracy of the increment ratio, is either the same or reduced, while increasing the number of attributes and instances. However, the J48 showed a slight increment for the state of care model but remained similar for the diagnosis model.

### B. EXPERT EVALUATION

The expert evaluation was performed using the FGD approach because FGD is one of the CDSS evaluation categories. The expert evaluations also took place at the same time as the system implementation evaluations, however, the statements presented here were exclusively concerning IDM. Table 11 shows three evaluation statements presented to twelve healthcare professionals in different specialities from AMDI, USM as respondents using the FGD method. The 12 respondents consisted of three paediatricians, two medical lecturers, a public health physician, a radiologist, a family physician, a surgeon, a transfusion specialist and two AMDI information technology officers.

The three evaluation statements address three main aspects of IDM-IDSS-healthcare acceptability. The three main aspects were the acceptance of the IDM concept in general healthcare, the acceptance of Diabetes IDM, and the acceptance of IDM-IDSS-healthcare to aid healthcare decision making. The evaluation was done using five scales as shown in Table 12. As a result, 75% of respondents strongly agreed; 25% agreed to accept the IDM concept of healthcare in general, according to Figure 11. Following, 83% of respondents strongly agreed; 17% agree to accept the Diabetes IDM. Conclusively, all of the respondents strongly agreed to accept the IDM-IDSS-healthcare to aid healthcare decision making in the healthcare system. These results showed that IDM-IDSS-healthcare is practically used in healthcare solutions.

### VI. CONCLUSION

This study has proposed an interrelated decision-making model for intelligent decision-making in healthcare based on the multi-agent solution. The proposed model shown is workable and proven by applying it to a diabetes case study. A diabetes IDM-IDSS consists of five interrelated stages of care: primary care, secondary care, tertiary care, quaternary care, and palliative care. The Diabetes IDM-IDSS model also successfully demonstrates the existence of in-and-out data flows at each stage. Furthermore, the case study has shown that each stage can have various types of decision-making. The experiment has shown two types of decision-making: diabetes diagnostic and stage of care in primary and secondary care.

Even though the experiment only focuses on two stages, the result shows how iterative decision-making works and how accuracy of prediction model changes due to additional instances toward time. This research also has found the impact on the effectiveness of decision making: type of decision making, the type of algorithm uses in modelling, the number of instances, and the number of attributes. The experiments result consistently show that adding some of the instances have increased the accuracy model. However, if the accuracy is already nearly or reaches 100%, the additional data does not
change. While additional attributes cause has to reduce the accuracy of the decision-making model.

It is because the model is more complex and needs more instances to reach high accuracy. In summary, it concludes that the proposed interrelated decision-making approach is applicable uses for future IDSS-healthcare solutions as it supports the dynamic change of data that influence the decision-making accuracy in any healthcare stage. Furthermore, the expert evaluation also agreed that the proposed IDM IDSS-healthcare model is an acceptable solution for healthcare decision-making.

Therefore, we conclude that the IDM-IDSS-healthcare model is acceptable and that it is recognized as an aid in the decision-making process, particularly in the healthcare sector. However, before uses it in the real-world needs more robust experiments using real diabetes treatment data using more recent machine learning algorithms. It can be concluded that, this model can be applied in other fields characterized by stages, such as various stage of decision making in business, etc.

ACKNOWLEDGMENT

The authors would like to thank the Ministry of Higher Education for financing and supporting this study under the Grant Project Code: LRGS/1/2020/UKM/01/5/2, with Associate Prof. Dr Zulaiha Ali Othman as the principal investigator.

REFERENCES

[1] R. Busse and M. Blümel, “Germany: Health system review,” Health Systems in Transition, vol. 16, no. 2, 2014.

[2] J. Cumming et al., “New Zealand: Health system review,” Health System in Transition, vol. 4, no. 2. 2014.

[3] Ministry of Health and Long-Term Care, “Preventing and managing chronic disease: Ontario’s framework,” Ontario, Canada, May 2007.

[4] S. A. Levenson, “The health care decision-making process framework,” Journal of National Library of Medicine, vol. 11, no. 1, pp. 13–17, 2010.

[5] J. Braithwaite et al., “Complexity science in healthcare—Aspirations, approaches, applications and accomplishments: A White Paper,” Australian Institute of Health Innovation, Macquarie University, Sydney, Australia, 2017.

[6] T. Kuehlein, D. Sghedoni, and G. Visentin, “Quaternary prevention: A task of the general practitioner,” Primary Care Care Journal, vol. 10, no. 18, pp. 350–354, 2010.

[7] Verywellhealth. Levels of Medical Care: Primary, Secondary, Tertiary and Quaternary Care. [Online] Available: http://patients.about.com/od/moreprovidersbeyonddocs/a/Stages-Of-Care-Primary-Secondary-Tertiary-And-Quaternary-Care.htm

[8] Education Centre, Office of the Chief Medical Information Officer (CMIO), Health Care 101 eBook, Ontario, Canada, 2013, pp. 1–15.

[9] F. Toth, “Classification of healthcare systems: Can we go further?” Health Policy Journal, vol. 120, no. 5, pp. 535–543, 2016.

[10] R. A. Greenes et al., “Clinical decision support models and frameworks: Seeking to address research issues underlying implementation successes and failures,” Journal of Biomedical Informatics, vol. 78, pp. 134–143, 2018.

[11] T. Rice et al., “United States of America: Health system review,” Health System in Transition, vol. 15, no. 3, 2013.

[12] Kwazulu-Natal Province, Health Republic of South Africa, Referral System: Levels of Health Care, Corporate Communication, November 2014. Accessed on: October 3, 2018 [Online] Available: http://www.kznhealth.gov.za/Referral-system.htm

[13] S. Grace et al., “The healthcare system is not designed around my needs’: How healthcare consumers self-integrate conventional and complementary healthcare services,” Complementary Therapies in Clinical Practice, vol. 32, pp. 151–156, 2018.

[14] J. Carneiro et al., “Group decision support systems for current times: Overcoming the challenges of dispersed group decision-making,” in Journal of Neurocomputing, vol. 423, pp. 735–746, 2021.

[15] Zhuang et al., “MEAN+R: implementing a web-based, multi-participant decision support system using the prevalent MEAN architecture with R based on a revised intuitionistic-fuzzy multiple attribute decision-making model” MicrosystTechnologies, vol. 10, pp. 4291–4309, 2018.

[16] B. Moorman, Thoughts on clinical decision support and its future: Dr. Greene’s Interview. March. 13, 2018. Accessed on: November 3, 2018 [Online] Available: http://medicalconnectivity.com/2018/03/13/clinical-decision-support-and-its-future/

[17] O. Babalola, “Consumers and Their Demand for Healthcare,” Journal of Health & Medical Economics, vol. 3(1), pp. 3–5, 2017.

[18] CGI Group Inc., “Healthcare Challenges and Trends,” The Patient at the Heart of Care, 2014.

[19] WHO, “Goals of a Healthcare System”, in Western Pacific Regional Strategy for Health Systems Based on the Values of Primary Health Care, pp.17-18, 2010.

[20] R. J. Taylor, B. R. McAvoy, and T. O’ Dowd, “General practice in perspective,” in General Practice Medicine, 1st ed., Edinburgh, UK: Churchill Livingstone, 2003.

[21] L. Kovacic et al., “Management in Health Care Practice” in A Handbook for Teachers, Researchers and Health Professionals, 1st ed. Forum for Public Health in South Eastern Europe, Programs for Training and Research in Public Health, Zagreb, Croatia, 2008, pp. 1–679.

[22] G. Spirdon, A. Sarbu and D. Carstoiu, “Computerised decision system for diabetes mellitus and associated complications—CODES,” IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR), Cluj-Napoca, Romania, May 24-May 26, 2018, pp. 1–4.

[23] K. Rajalakshmi, S. C. Mohan, and S. D. Babu, “Decision support system in healthcare industry”, International Journal of computer applications, vol. 26, no. 9, pp. 42-44.

[24] D. Quek, “The Malaysian health care system: A review,” Malaysian Medical Association, Kuala Lumpur, Malaysia, July 2014.

[25] N. Mahiddin, Z. A. Othman and A. A. Bakar, “A Framework for Kidney Disease Management System based on Decision Support System (DSS) Data Mining Approach,” in 2nd National Doctoral Seminar on Artificial Intelligence Technology (CAIT 2012), Residence Hotel, UNITEN, Malaysia, November 2012, pp. 105-109.

[26] N. Mahiddin, Z. A. Othman and A. A. Bakar, “A Sequence and Interrelated Decision Support System (DSS) for Healthcare,” in 3rd National Doctoral Seminar on Artificial Intelligence Technology (CAIT 2014), Faculty of Information Science and Technology, UKM, Malaysia, 22 November 2014, pp. 82-87.

[27] P. L. Barton, “Introduction to the US health services system,” and “An overview of the US health services system and its users,” Understanding the US Health Services System, 4th ed. Chapter 1 and Chapter 2. Chicago, Ill., 2010, pp. 3–45.

[28] S. et al., “Malaysia Health System Review,” Health Systems in Transition, vol. 3, no. 1, 2013.

[29] N. Mahiddin, Z. A. Othman and A. A. Bakar, “An architecture of multiagent system (MAS) for healthcare intelligent decision support system (IDSS),” Journal of Fundamental and Applied Sciences, vol. 9, pp. 144–167, 2017.

[30] C. Yang, T.-C. Chou and Y.-H Chen, “Bridging Digital boundary in Healthcare Systems — An Interoperability Enactment Perspective,” Journal of Computer Standards & Interfaces, vol. 62, pp. 43-52, 2019.

[31] W. Tomaszewski, “Computer-Based Medical Decision Support System based on guidelines, clinical pathways and decision nodes,” Acta of Bioengineering and Biomechanics Journal, vol. 14, no. 1, 2012.

[32] D. Arnott and G. Pervan, “A critical analysis of decision support systems research revisited: the rise of design science,” Journal of Information Technology, vol. 29, pp. 269–293, 2014.
[33] W. V. Melle, “MYCIN: a knowledge-based consultation program for infectious disease diagnosis,” *International Journal of Man-Machine Studies*, vol. 10, pp. 313–322, 1978.

[34] R. A. Miller et al., “INTERNIST-1, An Experimental Computer-based Diagnostic Consultant for General Internal Medicine,” *The New England Journal of Medicine*, vol. 307, no. 8, pp. 468–476, 1982.

[35] G. O. Barnett et al., “DXPlain: An Evolving Diagnostic Decision-Support System,” *Journal of American Medical Association*, vol. 258, no. 1, pp. 67–74, 1987.

[36] F. Zhou et al., “Overview of the New Types of Intelligent Decision Support System,” in *3rd International Conference on Innovative Computing and Information and Control (ICICIC),* Dalian, China, 18–20 June 2008, pp. 267–267.

[37] D. Kalra and D. Ingimundarson, “Electronic Health Records” in *Information Technology Solutions for Healthcare, Health Informatics, London*, Springer, 2006, ch. 7, pp. 135–181.

[38] A. Schneider and H. Feussner, “Health Informatics/Health Technology Information,” in *Biomedical Engineering in Gastrointestinal Surgery*, Academic Press, 2017, ch. 12, pp. 473–489, 2017.

[39] E. Davidson, A. Baird, and K. Prince, “Opening the envelope of health care information systems research,” *Journal of Information and Organization*, vol. 28, no. 3, pp. 140–151, 2018.

[40] H-T. Zhang, “New Trends for Decision Support Systems,” in *IEEE International Conference on Systems, Man, and Cybernetics, COEX, Seoul, Korea, 14-17 October 2012, pp. 1373-1378.

[41] H. Salem, G. Attiya and N. El-Fishawy, “A Survey of Multi-Agent based Intelligent Decision Support System for Medical Classification Problems,” *International Journal of Computer Applications*, vol. 123, no. 10, pp. 20-25, 2015.

[42] M. A. Kadhim, “FNDSB: a fuzzy-neuro decision support system for back pain diagnosis,” *Cognitive Systems Research Journal*, vol. 52, pp. 691–700, 2018.

[43] B. Malmir, M. Amini, and S. Chang, “A medical decision support system for disease diagnosis under uncertainty,” *An International Journal of Expert Systems with Application*, vol. 88, no. C, pp. 95–108, 2017.

[44] C. Casado-Lumbrares and A. R. Gonzalez, “PsyDis: Towards a diagnosis support system for psychological disorders,” *An International Journal of Expert Systems with Application*, vol. 39, pp. 11391–11403, 2012.

[45] T. P. Exarchos et al., “Mining balance disorder's data for the development of diagnostic decision support systems,” *Computers in Biology and Medicine Journal*, vol. 77, pp. 240–248, 2016.

[46] M. F. Soufi et al., “Decision support system for triage management: A hybrid approach using rule-based reasoning and fuzzy logic,” *International Journal of Medical Informatics*, vol. 114, pp. 35–44, 2018.

[47] E. Kilsdonk et al., “Uncovering healthcare practitioners’ information processing using the think-aloud method: From paper-based guideline to clinical decision support system,” *International Journal of Medical Informatics*, vol. 86, pp. 10–19, 2015.

[48] A. Wulff et al., “An interoperable clinical decision-support system for early detection of SIRS in pediatric intensive care using openEHR,” *Artificial Intelligence in Medicine Journal*, vol. 89, pp. 10–23, 2018.

[49] Z. Cai et al., “An intelligent Parkinson’s disease diagnostic system based on a chaotic bacterial foraging optimization enhanced fuzzy KNN approach,” *Journal of Computational and Mathematical Methods in Medicine*, vol. 3, pp. 1–24, 2018.

[50] A. Morales et al., “A decision support system for antibiotic prescription based on local cumulative antibigrams,” *Journal of Biomedical Informatics*, vol. 84, pp. 114–122, 2018.

[51] K. S. Gayathri and K. S. Eswarakumar, “Intelligent decision support system for dementia care through smart home,” in *Procedia Computer Science, 6th International Conference on Advances in Computing & Communications (ICACC)*, Cochin, India, September 6–8, 2016, pp. 945–955.

[52] R. Ali et al., “H2RM: A hybrid rough set reasoning model for prediction and management of diabetes mellitus,” *Science and Technology of Sensors Journal*, vol. 15, pp. 15921–15951, 2015.

[53] F. Ali et al., “A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion,” *Information Fusion Journal, Elsevier*, vol. 63, pp. 208–222, November 2020.

[54] F. Ali et al., “An intelligent healthcare monitoring framework using wearable sensors and social networking data,” *Future Generation Computer Systems Journal, Elsevier*, vol. 114, pp. 23–43, 2021.

[55] L. Aggarwal, P. Goswami, and S. Sachdeva, “Multi-criterion intelligent decision support system for Covid-19,” *Applied Soft Computing Journal*, vol. 101, pp. 107056–107070, 2021.

[56] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, “From data mining to knowledge discovery in databases,” *AI Magazine*, vol. 17, pp. 37–54, 1996.

[57] S. L. Hyland et al., “Early prediction of circulatory failure in the intensive care unit using machine learning,” *Nature Medicine Journal*, vol. 26, pp. 364–373, March 2020.

[58] G. van Valkenhoef et al., “ADDIS: A decision support system for evidence-based medicine,” *Decision Support Systems and Electronic Commerce Journal*, vol. 55, pp. 459–475, 2013.

[59] A. Baert et al., “A personal decision support system for heart failure management (HeartMan): Study protocol of the HeartMan randomized controlled trial,” *BMC Cardiovascular Disorders Journal*, vol. 18, pp. 186–195, 2018.

[60] A. Nakhai et al., “Studying the effects of systemic inflammatory markers and drugs on AVF longevity through a novel clinical intelligent framework,” *IEEE Journal of Biomedical and Health Informatics, vol. 24(1), pp. 3295–3307, November 2020.*

[61] Z. A. Othman et al., “Household Overspending Model Amongst B40, M40 and T20 Using Classification Algorithm,” *International Journal Of Advanced Computer Science and Applications (IJACSA),* vol. 11(7), pp. 392-399, 2020.

[62] N. Sani et al., “Drop-out prediction in higher education among B40 students,” *International Journal of Advanced Computer Science and Applications (IJACSA),* vol. 11(11), pp. 550–559, 2020.

[63] J. Han and M. Kamber, “Getting to know your data,” in *Data Mining: Concepts and Techniques, 2nd ed.* San Diego, CA: Morgan Kaufmann Publishers, 2011.

[64] S. K. Sarkar et al., “Machine learning for health (ML4H) 2020: Advancing healthcare for all,” in *Proceedings of the Machine Learning for Health NeurIPS Workshop (PMLR),* virtual, December 11, 2020, pp. 1–11.

[65] S. Piri et al., “A data analytics approach to building a clinical decision support system for diabetic retinopathy: Developing and deploying a model ensemble,” *Decision Support Systems Journal*, vol. 101, pp. 12–27, 2017.

[66] M. Dios et al., “A decision support system for operating room scheduling,” *Computer & Industrial Journal*, vol. 88, pp. 430–443, 2015.

[67] P. Lambin et al., “Decision support systems for personalized and participative radiation oncology,” *Advanced Drug Delivery Reviews Journal*, vol. 109, pp. 131–153, 2017.

[68] Z. Y. Zhuang, C. L. Wilkin, and A. Cegłowski, “A framework for an intelligent decision support system: A case in pathology test ordering,” *International Journal of Medical Informatics*, vol. 86, pp. 10–19, 2015.

[69] S. Nazari et al., “A fuzzy inference–fuzzy analytic hierarchy process-based clinical decision support system for diagnosis of heart diseases,” *Expert Systems with Applications Journal*, vol. 95, pp. 261–271, 2018.

[70] E. G. Price-Haywood et al., “Intelligent clinical decision support to improve safe opioid management of chronic noncancer pain in primary care,” *Applied Health Services Research, Ochsner Journal*, vol. 18, pp. 30–35, 2018.

[71] A. Singh and B. Pandey, “A new intelligent medical decision support system based on enhanced hierarchical clustering and random decision forest for the classification of alcoholic liver damage, primary hepatoma, liver cirrhosis, and cholelithiasis,” *Journal of Healthcare Engineering*, pp. 1–9, 2018.

[72] D. Calcatera et al., “A clinical decision support system to increase appropriateness of diagnostic imaging prescriptions,” *Journal of Network and Computer Applications*, vol. 117, pp. 17–29, 2018.

[73] C. Jin et al., “Intelligent system to predict intradialytic hypotension in chronic hemodialysis,” *Journal of the Formosan Medical Association*, vol. 117, pp. 888–893, 2018.
[74] P. D. Leedy and J. E. Ormrod, “Part III: Research designs,” in Practical Research Planning and Design, 9th ed. New York, NY: Pearson Education Incorporation, 2019, pp. 146–301.

[75] S. Brahman and L. Jain, “Intelligent decision support systems in healthcare,” Advanced Computational Intelligence Paradigms in Healthcare 5, vol. 326, pp. 3–10.

[76] S. Itani, F. Lecron, and P. Fortemps, “Specifics of medical data mining for diagnosis aid: A survey,” An International Journal of Expert Systems with Applications, vol. 118, pp. 300–314, 2019.

[77] D. F. Lobach, “Evaluation of clinical decision support,” in Clinical Decision Support Systems Theory and Practice, 3rd ed. Switzerland: Springer, pp. 147–161, 2016.

[78] K. Morikawa, and K. Takahashi, “Scheduling appointments for walk-ins,” International Journal of Production Economics, vol. 190, pp. 60-66, 2017.

[79] R. Burdett and E. Kozan, “An integrated approach for scheduling health care activities in a hospital,” European Journal of Operational Research, vol. 264(2), pp. 756-773, 2018.

[80] A. Saremi et al, “Appointment scheduling of outpatient surgical services in a multistage operating room department,” International Journal of Production Economics, vol. 141, pp. 646-658, 2013.

[81] O. M. Araz, D. Olson and A. R-Nafarrate, “Predictive analytics for hospital admissions from the emergency department using triage information,” International Journal of Production Economics, vol. 208, pp. 199-207, 2019.