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A novel report generation approach for medical applications: The SISDS methodology and its applications

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ABSTRACT

Background: Despite exciting innovation in information system technologies, the medical reporting has remained static for a long time. Structured reporting was established to address the deficiencies in report content but has largely failed in its adoption due to concerns over workflow and productivity. The methods used in medical reporting are insufficient in providing with information for statistical processing and medical decision making as well as high quality healthcare.
Objective: The aim of this study is to introduce a novel method that enables professionals to efficiently produce medical reports that are less error-prone and can be used in decision support systems without extensive post-processing.
Methodology: We first present the formal definition of the proposed method, called SISDS, that provides a clear separation between the data, logic and presentation layers. It allows free-text like structured data entry in a structured form, and reduces the cognitive effort by inline editing and dynamically controlling the information flow based on the entered data. Then, we validate the usability and reliability of the method on a real-world testbed in the field of radiology. For this purpose, a sample esophagus report was constructed by a focus group of radiologists and real patient data have been collected using a web-based prototype; these data are then used to build a decision support system with off-the-shelf tools. The usability of the method is assessed by evaluating its acceptability by the users and the accuracy of the resulting decision support system. For reliability, we conducted a controlled experiment comparing the performance of the method to that of transcriptionist-oriented systems in terms of the rate of successful diagnosis and the total time required to enter the data.
Result: The most noticeable observation in the evaluation is that the rate of successful diagnosis improves significantly with the proposed method; in our case study, a success rate of 81.25% has been achieved by using the SISDS method compared to 43.75% for the transcriptionist-oriented system. In addition, the average time required to obtain the final approved reports decreased from 29 min to 14 min. Based on questionnaire responses, the acceptance rate of the SISDS methodology by users is also found to outperform the rates of the current methods.

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Conclusion: The empirical results show that the method can effectively help to reduce medical errors, increase data quality, and lead to more accurate decision support. In addition, the dynamic hierarchical data entry model proves to provide a good balance between cognitive load and structured data collection.

1. Introduction

A medical report can be defined as the results of a medical examination of a patient or a written document describing the findings of a patient. They constitute the primary means of communication between laboratory professionals and referring physicians [1,2]. Medical reports facilitate the decision making process of the referring physicians, and enable them to provide a better health care service for their patients [3].

With emerging technologies and ever increasing need for accessibility and ease of use, the process of producing and disseminating medical reports started to be computerized; medical departments have made an effort to achieve a goal of collecting data in a structured format. Sittig et al. indicate that one major obstacle to the success of computer systems in medical reporting and diagnostic decision support is that of difficulty in entering data and consequently the acquisition of intact knowledge in processable format that can be put to better use in clinical research and health care management [4]. Some of the very earliest computerized medical reporting attempts focused on developing specialized terminals that allow physicians to produce reports with predefined coded forms [5]. The main reason for such an approach was to reduce human errors. However, the very sophistication of the concept causes the interface to be rather complex [1] that leads to loss of cognitive focus during both input and review processes [4]. Although there exist approaches that are cognitively less demanding, such as dictation by speech recognition, the reduction in the cognitive effort comes at the expense of structure and completeness. The resulting reports are usually in unstructured format, mostly free-text, and incomplete since details are assumed to be common knowledge and left out [6,7]; this, not surprisingly, leads to lack of standardization [7,8] and requires additional, and in general tedious, processing steps to prepare the data for further analysis and use (for example, in diagnostic decision support systems). Furthermore, clinicians frequently expressing concerns that interpretations in medical reports are often not relevant to the clinical questions they seek to answer and laboratory professionals often complaining of inadequate information from clinicians requesting the studies, existing reporting approaches seem to be insufficient in establishing the required communication medium between them [9,2,10]. A report by the Institute of Medicine also lists inadequate methods for generating and relaying information as one of several potential causes of medical errors [11].

In this study, our aim is to develop a novel method that overcomes the deficiencies of most prominent existing approaches. Our focus is on reducing the cognitive load without compromising the collection of data in structured form which is easy to process and manipulate. The method that we propose is referred as SISDS, the "Structured, Interactive, Standardized, and Decision Supporting Method".

2. Methodology

2.1. Background

As a first step of creating an effective medical reporting system, we first evaluated the most prominent approaches, namely handwriting, telephone access, transcriptionist-oriented systems, real time transcriptionist-oriented system (RTTOS), dictation by speech recognition (DBSR) and all structured data collected in a screen (ASDCIAS), in terms of their advantages and disadvantages. These approaches except ASDCIAS mostly depend on free-text format. Reports are generated manually, conventionally ink on paper in handwriting. Telephone access includes voice records recorded by report generators themselves in digital (or analog) format and data can be accessed with specific patient numbers using telephones or computers. In transcriptionist-oriented systems, the recorded reports are then transcribed by transcriptionists using computer terminals. In RTTOS and DBRS, reports are transcribed in real-time, either by transcriptionists or speech recognition software, by interacting with the person generating the report. The ASDCIAS approach aims to collect structured data that using a standardized set of concepts in a predefined format on a screen supported by sub screens, buttons, combo-boxes, etc. Structured data collected in ASDCIS approach are mainly aimed to be used for further research rather than a good care for patients.[1]

After analyzing several studies [2,4,5,8,9,13–17], we identified 14 important evaluation criteria presented in Table 1 and rated different approaches based on the degree that they satisfy each criterion; the rating scale ranged from "relatively high" to "relatively low" with five levels. These evaluation criteria are determined by consolidating various aspects of different approaches that are frequently mentioned in the references, albeit in different terms; they cover different needs of all the actors in the field such as laboratory professionals, examining physicians, institutions, patients, government and health insurance companies. This evaluation forms the basis of the software requirement analysis which consists of architectural, structural, behavioral and functional requirements.

It is easy to see that all of these approaches have some strengths as well as deficiencies when compared to each other and furthermore, none of them succeeds to provide a satisfactory answer to majority of the criteria (see [12] for a detailed discussion). Note that, structured methods are

[1] Interested reader can reach more detailed information about existing approaches from our technical report [12].

Table 1 – General evaluation of the handwriting (HW), telephone access (TA), transcriptionist-oriented systems (TOS), real time transcriptionist-oriented system (RTTOS), dictation by speech recognition (DBSR) and all structured data collected in a screen (ASDCIS) approaches in terms of advantages and disadvantages. rating: relatively low: −−, low: −, moderate: 0, high: +, relatively high: ++.

Criteria	HW	TOS	RTTOS	TA	DBSR	ASDCIAS
Cost effective (money)	++	−	−−	0	0	0
Quality of care	−−	0	0	−	0	0
Patient safety	−	−−	0	+	0	+
Report completeness	−−	0	0	0	0	+
Retrospective study/research	−−	−	−	−	−	++
Teaching	−−	−	−	−	−	+
Establishment of DDSS	−−	−−	−−	−−	−−	0
Public health	−−	−−	−−	−−	0	+
Reducing cognitive load	++	0	0	−	−	−−
Quick preparation	0	0	+	++	0	−−
Rapid dissemination/access	−−	−−	0	+	+	+
Reducing look-away problem	−−	+	+	++	−−	−−
Not needing a extensive computer knowledge	++	++	++	−	−	−−
Privacy	−−	−	−	−	++	++

found ineffective in reducing the cognitive load and suffer from the look-away problem that emerges when the process of examining patients or images is frequently interrupted with other tasks [2]. Furthermore, they require extensive computer knowledge and it takes more time to prepare the reports. On the other hand, in more simpler and less structured approaches, report completeness becomes an issue and privacy concerns arise; they also cannot provide satisfactory means for retrospective study and research, and further analysis. An important observation is that, in most cases, the criteria that different approaches perform well are complementary to each other; this indicates that an ideal reporting method, which is both effective and with less cognitive pressure, should be in between free-text reporting and sophisticated menu-driven structured approaches, providing a through communication among professionals, and also facilitating high level operations, such as population based inferences and decision support. We seek to achieve this by introducing (i) an interactive walk over the nested and hierarchical structure of a medical report during the editing process with better data-driven derivation, and (ii) a clear separation and abstraction between the underlying related data, possible operations over this data and its presentation.

2.2. *The SISDS method*

In the SISDS method, a medical report consists of a set of data groups. Each data group encapsulates data entries that are related to each other, and each data entry contains one or several data fields. The data is entered and the report is constructed by editing the values of these fields. Although the structure of a report is well defined, it is not fixed and changes dynamically as data groups and data fields are activated or deactivated based on the interactions of the user with the elements of the report. The basic conceptual decomposition of a report is presented in Fig. 1.

The building block in SISDS is a *data field* that holds a particular value. When we consider a typical esophagus radiology report, observations about the shape of the mucosal relief, the section, length and the site of the narrowness of esophagus are all examples of a data field. In order to be able to extract medical data out of a medical report, the data fields that it contains must be consistent and well defined, i.e. each data field must have a specific nominal, numeric or textual datatype. By assigning default values and defining constraints over them, for example, a permissible range or set of values, the cognitive load can be reduced and erroneous inputs can be prevented. Based on these observations, we define a data field as a tuple $\langle var, type, val, opts\rangle$ where *var* is the name of the data field, *type* is its type, *val* is its initial value, and *opts* is a list of options. *type* is either one of pre-defined types, such as integer, float, string, date, length, weight, volume, etc., or if it is a nominal variable it is a set of possible values, ex. $\{male, female\}$ for representing the sex of the patient. For measurement data types, such as length, the initial value should also contain the unit of measurement, ex. 1.2 cm. Explicitly stating the unit of measurement enables unit conversion, which facilitates information sharing. *opts* is a set of pairs of the form $\{\langle name_1, val_1\rangle, \ldots \langle name_n, val_n\rangle\}$ where $name_i$ denotes the name of the *i*th option and val_i is its value; typical options include the minimum, maximum and normal values of a variable. The options of a data field can be empty.

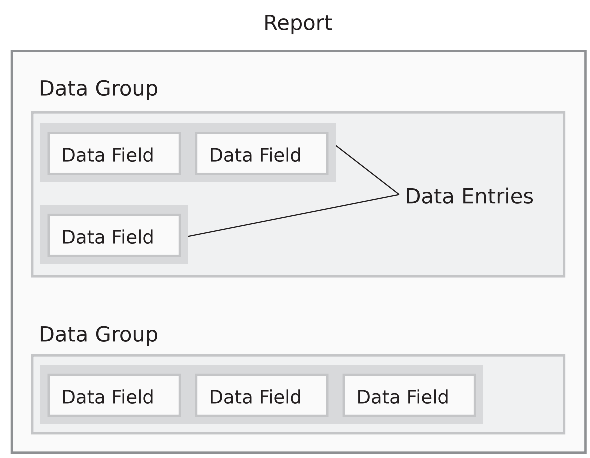

Fig. 1 – The elements of a medical report in the SISDS method.

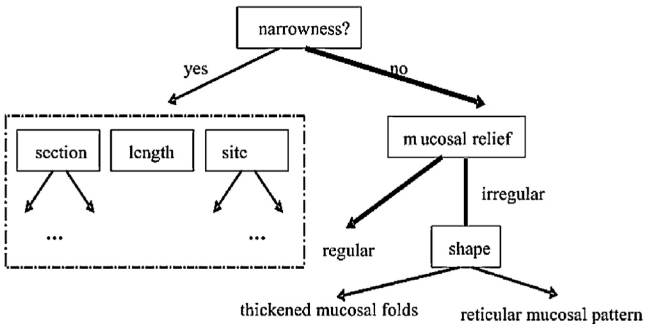

Fig. 2 – The hierarchical structure. Boxes correspond to data entries and line labels indicate possible answers. The dashed box groups a set of data entries that are activated when there is narrowness. The normal values are shown with thick edges.

A *data entry* is a unit of data request and encapsulates one or more data fields. In the example in Fig. 2, the information about the narrowness of the esophagus, which includes its section, length and site, is an example of a data entry with three data fields. A data field is defined by a tuple ⟨*label*, *vars*, *defs*⟩ where *label* is a unique identifier denoting the data entry, *vars* is a set of data field definitions and *defs* is a set of *data view* definitions. The idea behind data views is to allow different presentations of the same data entry based on user requirement; for example, in a tabular form or in a natural free-text like style. Each data view definition is a tuple of the form ⟨*type*, *lang*, *def*⟩ where *type* denotes its type, *lang* denotes the language of the definition, and *def* is the body of the definition. The *lang* attribute allows different data views be chosen for a data entry based on the specified language and rendered accordingly; this brings support for report generation in multiple languages without requiring natural language processing methods, which are not reliable and liable to medical errors. The body of the definition is an arbitrary text with embedded variable references of the form ⟨*var*, *vals*, *opts*⟩ where *var* is the name of the variable, *vals* is a set of mappings that map possible values of the variable to string counterparts (this is especially useful for nominal values), and *opts* is a set of options as in the definition of variables. Typical options include format specifiers to determine the rendering of the variable (display format, default unit, etc.). Note that, for consistency the definitions of all data views of a data entry should contain references to the same set of variables. Data view definitions are used by the presentation layer to render data entry forms or reports based on their *type*; for example, in nested tabular form or textual report format. This allows data collection and visualization to be handled similarly in a unified way.

In a medical report, only a subset of data entries may actually be relevant when entering data for a particular case. Let us consider the following question which is frequently found in an esophagus report: "*Is there any narrowness without a clear expansion in the esophagus during the transition of the contrast media?*". Usually, the answer to this question is *no*, and in this case the mucosal relief should be entered, which can be either *regular* or *irregular*; if the mucosal relief is irregular then the shape of the irregularity should also be specified; otherwise, this information is not required. In case there is a narrowness, that is the answer is yes, mucosal relief is not important and a completely different set of information should be entered including and depending on the properties of the narrowness. Note that, this inherently leads to a nested and hierarchical structure as depicted in Fig. 2 that emerges as a common feature of almost all kinds of medical reports [8], such as the esophagus report in our study.

One major drawback of this setting is the increased complexity due to the combinatorial expansion. A possible solution would be to reduce the number of active data entries that are being displayed to the user by interactively walking only on the necessary steps while completing the report, that is by following a path on the hierarchy. This is possible as the data entered at a certain point determines the information flow, and consequently, the related data that should be entered. For example, in the example in Fig. 2, it is unnecessary to ask for or display anything related to narrowness unless the user explicitly indicates that it exists. We would like to note that the dependencies between data fields may be more complex, i.e. the condition of requesting a certain information may also depend on the values of various other data fields that may or may not be dependent on each other. An effective structured reporting method should be able to address this requirement.

In the SISDS method, we introduce the notion of a *data group* for this purpose. As the name implies, a data group groups together related items and is defined by a tuple ⟨*label*, *data-entries*, *triggers*⟩. The *label* attribute uniquely identifies the data group. *data-entries* is a list of data entries of the form ⟨de_1, de_2, ..., de_n⟩ where de_i denotes the ith data entry as defined above. *triggers* is a set of triggers that activate data groups that are defined under the current data group, as well as activate expert opinions and advices that are defined for various specific conditions. Each trigger in *triggers* is a pair of the form ⟨*condition*, *action*⟩ where *condition* is a boolean expression with embedded variable references and *action* specifies an action to be executed when the condition holds, that is the boolean expression evaluates to true. The boolean expression may include arithmetic and logic operators, function calls, constants and variables references. The variable references in the boolean expression are of the form ⟨*label*, *var*⟩ where *var* is the name of the variable and *label* is the identifier of the data entry that the variable belongs. The variable references are not restricted to refer to the variables that belong to the data entries in *data-entries*. While evaluating the boolean expression, the variable references are replaced with the current value (default or that entered by the user) of the corresponding variables. Note that, the values of the variables with measurement data types must be normalized, i.e. converted into a common unit, before evaluation since the unit of such variables may be altered by the user during data entry. This can be done by automatically calling a unit conversion function while evaluating the condition expression.

An *action* can be either (i) a list of labels that denote the data groups to be activated leading to a tree like hierarchical structure, (ii) a message to be displayed, (iii) a diagnosis prediction, or (iv) constraints on the values of other variables depending on the triggered condition. Once a data group is

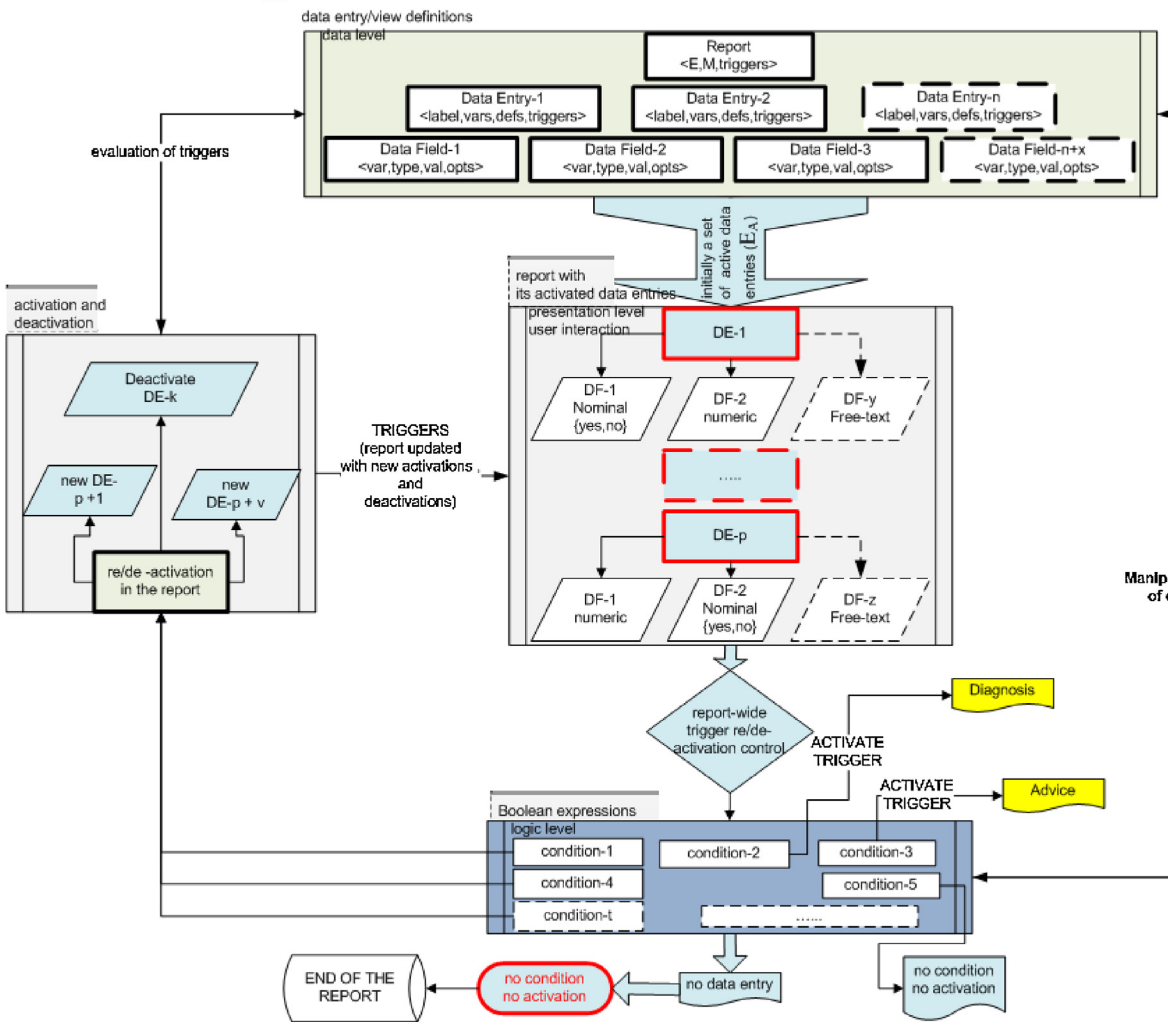

Fig. 3 – The interaction and information flow between the data, logic and presentation layers. All triggers are evaluated to update the report when the user enter a value for any data entry.

activated all of its data entries are displayed to user; similarly, they become hidden when the data group is deactivated. It is important to note that cyclic activations are not allowed, that is a descendant of a data group should not re/de-activate it via its triggers, to prevent inconsistencies. This triggering mechanism together with the actions effectively form the logic layer that functions as a gateway between the data and the presentation layers and separate them neatly.

Finally, a *report* is tuple ⟨G, M, *triggers*⟩ where G is a set of consistent data groups, that is all data groups referred in their trigger conditions and associated data entries exists in the report (i.e. are contained in G), M is an ordered list of data group identifiers denoting the *main data groups* that are initially activated, and *triggers* is a set of report-wide triggers; for each identifier in M there must be a corresponding data group in G. The main data groups constitute the initial skeleton of the report. The report-wide triggers enable to provide rule-based diagnosis and other suggestions to the user based on the entered data. Furthermore, overall consistency of reports can be checked by these triggers.

From a conceptual point of view, our structured design with interactivity looks like a tree with branches growing from a stem such that the branches collapse and expand on-demand; the data entries in the main data groups form the initially expanded branches. A dynamic hierarchy of *sections* is built as related data entries logically follow-up depending on the defined conditions. The interaction and information flow between the data, logic and presentation layers in the proposed method is depicted in Fig. 3. We would like to point out that several existing design patterns, most notably the model-view-controller (MVC) architectural pattern fits well to this layering [18].

In order to verify the eligibility of the proposed approach, we implemented a web-based prototype based on the client–server architecture. The prototype has two main components, the front-end that is used to enter data for generating reports, and the back-end that allows privileged users to easily define and edit reports and their structure, as well as export collected data for analysis purposes; all information is stored in a relational database. The web server renders the report

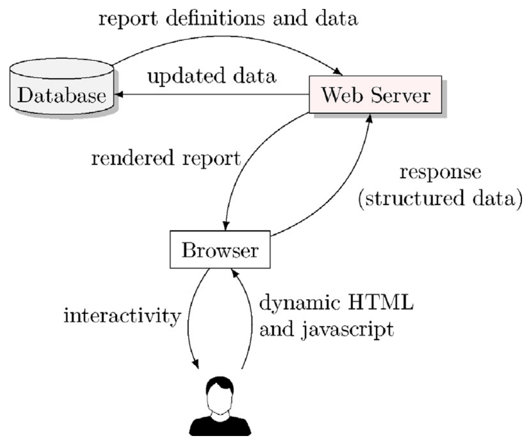

Fig. 4 – The architecture of the web-based prototype.

Table 2 – The syntax of variable, data entry/view definitions and trigger conditions in modified BNF notation.

⟨variable⟩ → ⟨name⟩ = ⟨type⟩ {**:** ⟨value⟩} {**;** ⟨opts⟩}
⟨type⟩ →**int**|**float**|**string**|**date**|**length**|**area**|**volume**| ⟨nominal⟩
⟨nominal⟩ → ⟨value list⟩
⟨value list⟩ → ⟨value⟩ | ⟨value⟩ **,** ⟨value list⟩
⟨opts⟩ → ⟨opt⟩ = ⟨value⟩ | ⟨opt⟩ = ⟨value⟩ **,** ⟨opts⟩
⟨defn⟩ → ⟨entity⟩ | ⟨entity⟩ ⟨defn⟩
⟨entity⟩ → ⟨string literal⟩ | ⟨var ref⟩
⟨var ref⟩ → **[** {⟨label⟩**.**} ⟨name⟩ {**:** ⟨value map⟩ } {**;** ⟨opts⟩ }**]**
⟨value map⟩ → ⟨value⟩ = ⟨string literal⟩ |
⟨value⟩ = ⟨string literal⟩ **,** ⟨value map⟩

for data entry or viewing, which is then displayed to the user by the web browser; the user interacts with the web browser (via Dynamic HTML and AJAX) and the feedback of the user (data entry or update, if any) is sent back to the web server for processing (Fig. 4). The stored data in the database can be extracted in various formats that can be easily processed by third-party applications, such as decision support systems and statistical packages.

In realizing the abstract variable, data entry and data group definitions given in the previous section, we opted to use a user-friendly (human-readable) textual notation with a simple syntax; the syntax of this notation is presented in Table 2 together with some examples in Table 3: the sections in curly brackets are optional. Each variable has a name as well as a type. For nominal variables, the type attribute is a comma separated list of possible values of the variable, such as *male, female*. An optional initial value might as well be defined for each variable. Every data entry has a unique number indicating itself and the data fields belonging to the data entries can be referred in dotted notation as [the unique number of the data entry].[the name of the data variable]. The options are defined as a list of the form [the name of the option]=[the value of the option]. The data request/view definitions (defn) are arbitrary strings that contain variables references (var ref). For nominal variables, the variable references in data view definitions may contain value mappings that map possible values of the variable into textual form depending on the language of the definition. For example,

Table 3 – Two data view definitions in different languages and an example condition. In the data view definitions, note the change in the position of the variable in the Turkish version.

segment_length = length: 2 cm; min = 0 cm, max = 10 cm What is the length of the narrow segment? *[segment_length]* The length of the narrow segment is *[segment_length]*. Dar segment genişliği *[segment_length]*'dir. (in Turkish)
defect = smooth,regular,circular: smooth; normal = regular The filling defect is in the shape of *[defect:smooth=smooth linear,circular=circular modular, regular=regular linear]* structure. Dolma defekti *[defect:düz=düz linear,yuvarlak=yuvarlak modüler,düzenli=düzenli linear]* yapıdadır. (in Turkish)
(*[q1.segment_length]* >5 and *[segment_length]* <7) or *[defect]* = "circular"

the variable reference 5.*sex:male=bay,female=bayan* indicates that the *sex* variable belonging to the data entry with label 5 should be displayed as *bay* or *bayan* depending on its value; bay and bayan mean male and female in Turkish, respectively. The optional *opts* attribute allows to specify how the variable should be rendered, ex. the number of significant digits for numerical variables.

The main novelty of this particular implementation is a free-text like data entry facility with *inline editing*. As we mentioned in the previous section, free-text is the most natural way for data entry where the entered data directly corresponds to the content of the final product (i.e. report). One way to ensure this in structure data entry is to let the user see the resulting report while *still entering data*. Although this can be accomplished by following a split view approach, i.e. having separate data entry and report views and updating the second one as the user makes modifications in the first one, it is not cognitively appealing as the user has to go back and forth between different views, increasing the cognitive load. The solution that we offer is to use inline editing, that is to present the report in a single view but allow the users to directly manipulate the data on the screen simply by clicking on data fields which are displayed as hyperlinks (Fig. 5): the possible values are listed when the user clicks on a hyperlink of a nominal field, such as to enter the narrowness as "there is" or "there isn't" in Fig. 5; a text entry together with a list of corresponding units is displayed for numeric fields, and the entered values are automatically verified. As the user changes the values of the variables, the contents of the report is also rearranged according to the predefined trigger conditions. The trigger conditions are evaluated by an interpreter written in Javascript and runs on the client side. While evaluating the boolean expressions, the interpreter replaces variable references by the current values of the corresponding variables and also performs unit conversion if necessary. It also notifies the user when the conditions associated with the report-wide notifications/rule-based diagnostic suggestions hold.

According to some studies about visual cognition, under normal viewing conditions only a minor part of the environment is encoded in detail [19]: although the factors that determine which features of a scene are encoded remain unknown, it seems likely that attention plays a major role. Sometimes professionals could not see other pertinent details

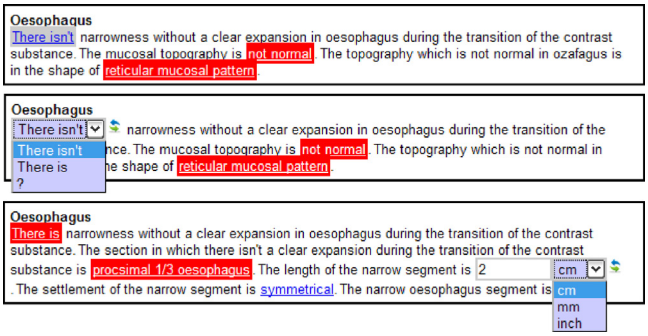

Fig. 5 – Inline data entry in free-text format. (top) Initial state. Abnormal values are highlighted in red, and the field yet to be entered has a gray background. (middle) When the user clicks on the link inline editing is activated. (bottom) The new value "There is" triggers another set of data entries. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

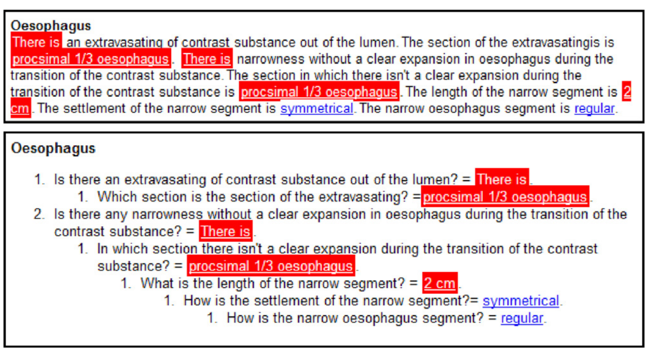

Fig. 6 – Two different views of the same report. Free-text (top) and enumerated (bottom).

while concentrating on a specific subject. In order to prevent this, in our implementation the presentation layer is enriched with visual clues; data fields having abnormal values or yet to be entered are highlighted in different ways to warn the user and draw his attention to those sections of the report (Fig. 5). The prototype also allows users to temporarily hide data entries that are not directly related with a selected data entry (i.e. show only selected data entry together with its descendants and those that are involved in the activation of this data entry).

Besides free-text like data entry, by taking advantage of the separation of data from its representation, the prototype also supports data entry in the form of a nested enumerated list (Fig. 6) and additional formats can be added with ease. These are just different representations of the same data, albeit with different cognitive properties, and it is possible to switch from one to another online during editing; even though the first one is more natural, the enumerated list may be more convenient and preferable in certain cases – especially when one is interested in seeing the hierarchical structure which is hidden in the first one. In both modes, the reports can also be edited and viewed in multiple languages.

A demo version of the prototype is available online at http://www.gata.edu.tr/mebs/sisds for hands-on experience.

2.3. *Evaluation of SISDS*

We have validated the usability and reliability of the SISDS method based on three criteria:

1. the acceptability of the methodology by the users who entered reports with the system,
2. whether the stored data can be used effectively for designing diagnostic decision support systems without tedious data preprocessing steps, and
3. the performance of the proposed approach compared to the existing approaches.

As a real-world testbed for the proposed methodology, we selected the field of radiology and a sample esophagus report is constructed by a focus group of radiologists using the web-based prototype. The overall structure and more detailed information about the sample esophagus report can be found in the supplementary material of the manuscript. The esophagus report is prepared by consulting 12 radiologists working in six different hospitals, five of whom are the head of their departments. There is a lack of standards and a lack of consensus on proposed standards in medicine. Therefore, the radiologists had different insights about the details of the report and hence reaching a consensus turned out to be a nontrivial task. The consensus about the format of the report has been reached by referring to the book by Weissleder et al., in which a comprehensive study of esophagus report is included as a textbook [20], with some minor modifications requested by the radiologists.

The resulting esophagus report consists of 13 main and 59 auxiliary data entries in a hierarchy having a maximum depth of 4. Each main data entry has a single nominal variable, and the report contains a total of 72 variables (53 nominal and 19 numerical) making it a fine example of a moderate sized medical report. After filling in the report, at least one diagnosis (up to 4) must be entered according to the ICD-10 coding scheme.[2] In a period of six months, health care professionals from the radiology departments of four different hospitals[3] retrospectively entered real patient esophagus reports using the web-based prototype. The resulting data set contains 1240 instances spanning a period of six years from 2003 to 2008. The age/sex distribution of population is 47.87% male, 52.13% female with a minimum age of 1 and a maximum age of 87 (Fig. 7a). In the data set, 717 instances (57.8%) belong to healthy patients and remaining 540 instances (42.4%) were tagged by one or more diagnoses. The number of distinct ICD-10 codes was 39. Among them only three were significant: K21.9 (250

[2] The International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) is a coding of over 155,000 diseases and signs, symptoms, abnormal findings, complaints, social circumstances and external causes of injury or diseases, as classified by the World Health Organization (WHO).

[3] These hospitals are Hacettepe Medical University, Medicana International Hospital, Gülhane Military Medical Academy and Baskent University.

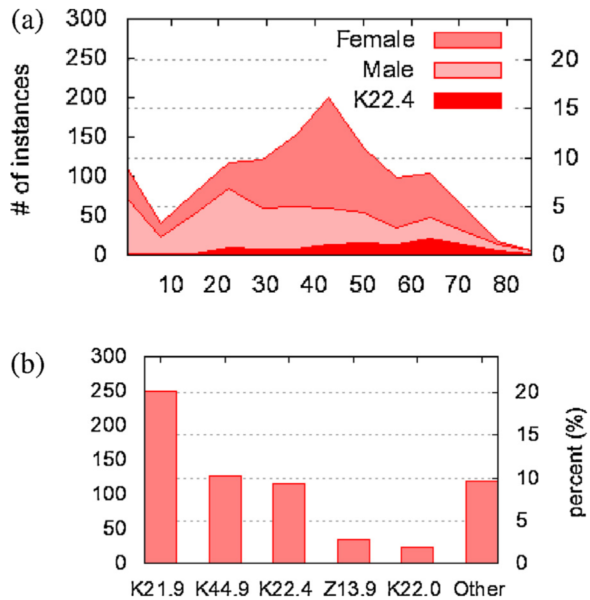

Fig. 7 – (a) The age distribution of the data set for different sexes and the target diagnosis. (b) The distribution of ICD-10 diagnoses in the data set.

instances, 20%), K44.9 (126 instances, 10%) and K22.4 (116 instances, 9.4%); the remaining ones have an average of 4.9 instances (Fig. 7b).

In order to measure the acceptance of the SISDS method, we conducted a survey among the radiologists and clinicians who have used the prototype during the data collection period. A questionnaire is prepared with clear, succinct, and unambiguous close-ended multiple-choice type questions supplied by a group of statisticians, radiologists and physicians following the design patterns in [21–24]; the complete list of questions is available in the supplementary material of the manuscript. The aim of the questionnaire was to observe the essential aspects of both an ideal medical reporting system, such as faster response to physician's clinical orders, and a computer system, such as maintenance and support cost. The questions compare the proposed method to the handwriting, telephone access, transcriptionist-oriented systems, RTTOS, DBSR and ASDCIAS approaches in various aspects that include: cognitive load, productivity, reducing medical error and improving patient safety, management of knowledge, data quality and user-friendliness. Another objective of the questionnaire was to measure the satisfaction of the related actors and to some extent, patients based on the answers entered by the physicians. Moreover, the degrees that SISDS covers the criteria of *electronic performance support systems* and *learning organizations* are also of interest. For each criteria, correlated questions are prepared in order to reduce the bias or social mask[4] and check consistency. The distribution of the questions in the questionnaire by criteria is presented in Table 4; the average number of questions in each criteria was about 7 (7.3 ± 3.2). Quantitative information is collected using a rating scale from −2 to +2; +2 denotes strong positive attitude, −2 denotes strong negative attitude and 0 represents "no idea or neutrality". The questionnaire has been applied to 20 physicians after they became accustomed to using the web-based prototype of the SISDS method; 12 of whom were radiologists (4 of them being the head of their departments) and 8 of whom were clinicians. All physicians (3 full prof., 5 assoc.prof., 6 assist.prof., 6 specialists) were accustomed to the different approaches mentioned above.

In order to verify whether the data collected by using the SISDS approach can be used effectively for designing diagnostic decision support systems without tedious data preprocessing steps or not, we built one based on the collected esophagus data using off-the-shelf machine learning tools. Our goal, that is to predict a particular diagnosis for new esophagus reports given a set of existing ones, is a classical binary classification problem; hence, it is possible to employ various well-known classification techniques that are compatible with the properties of the data set. For this purpose, we used the popular Waikato Environment for Knowledge Analysis (WEKA) application suite developed at the University of Waikato that provides a collection of visualization tools and algorithms for data analysis and predictive modeling.[5]

In our experiments, we focused on four specific representatives of different classification techniques: a Bayesian network that uses hill-climbing and a simple estimator that estimates probabilities directly from the data, a multinomial logistic regression model with a ridge estimator, a support vector machine with sequential minimal optimization algorithm, and an alternating decision tree. We trained instances of these classifiers using WEKA and evaluated their accuracy. In order to prevent over-fitting, we applied 10-fold cross-validation. To reduce variability, multiple rounds (in our case, again 10) of cross-validation are performed using different seeds, and the validation results are averaged over the rounds. In logistic regression model and support vector machine classifiers, the nominal attributes are transformed into binary numeric attributes and normalized. Although we will mainly be presenting the results on a sample data set (in the next section), the followed procedure is general and similar studies can be conducted on other domains as well.

In order to evaluate the reliability and the performance of the proposed SISDS approach, we compared its real-life use with the most widespread approach, transcriptionist-oriented systems. 10 esophagus DICOM images out of 253 esophagus DICOM images belonging to real patients[6] were selected. Among these 10 images, 8 of them were not normal and 2 of them indicated a diagnosis of K22.4. Each of 8 radiologists generated reports of these 10 DICOM esophagus images first by using the transcriptionist-oriented approach without being accustomed to using the SISDS approach and then by using the SISDS approach after being familiar with it. For each

[4] The term of social masks is generally used for concealing some facts: for example, unsatisfied people may tend to present a positive image for some of the approaches, not only to others but also to themselves [22].

[5] WEKA is freely available from http://www.cs.waikato.ac.nz/ml/weka/.

[6] These images were provided by the radiology departments of Turkish Oncology Hospital and Yüksek Ihtisas Hospital.

Table 4 – The results of the questionnaire. The rating for each item ranges from −2 (lowest) to +2 (highest). The results are averaged over the rounds.

Criteria for approaches	# of ques	HW	TOS	RTTOS	TA	DBSR	ASDCIAS	SISDS
Quality of care	10	−2	−1	0	−1	0	1	2
Data quality	6	−2	−1	0	0	0	1	2
Management of knowledge and DSS	12	−2	−2	−2	−2	−2	1	2
Research	3	−2	−2	−2	−2	−2	1	2
Reducing medical error and improving patient safety	13	−1	−2	0	1	0	2	2
Cognitive overload	7	2	2	0	1	−1	−2	1
Distribution time (faster response)	7	0	−2	1	2	0	1	1
Overall cost	6	2	−1	−2	0	1	1	1
Educational/training	10	−2	−1	−1	−2	−1	0	2
User-friendly	3	2	2	1	1	0	−1	1
User-productivity (number of reports/time)	3	2	−1	1	1	0	−1	1
Patients' satisfaction	5	0	−2	1	0	1	−2	1
Satisfaction of referring physicians	6	−1	−2	0	−2	0	1	2
Satisfaction of laboratory professionals	6	1	1	2	1	0	−2	1
EPSS	11	−2	−2	−2	−2	−1	0	2
Learning organization	10	−2	−1	−1	−2	−1	0	2
Overall benefits (total)		−7	−15	−4	−6	−6	1	25

participant, there was at least a period of one week between these two phases, and the radiologists did their routine works generating other reports during in between. In addition to this, the names in the DICOM images were anonymized and the order of the images was randomized. Thus, the radiologists were not able to compare the findings in the images while entering data for the same images in both systems. We analyzed both approaches based on two criteria: the total time required to enter data, and the rate of successful diagnosis.

Table 5 – The average prediction accuracy of regular and cost-sensitive versions of the classification algorithms for the K22.4 diagnosis.

	Healthy	K22.4	Overall
Regular			
ADTree	98.24 ± 0.0002	76.21 ± 0.0102	96.19 ± 0.0001
BayesNet	97.34 ± 0.0002	56.30 ± 0.0316	93.52 ± 0.0001
Logistic	97.64 ± 0.0008	77.67 ± 0.0473	95.77 ± 0.0013
SMO	98.61 ± 0.0001	78.43 ± 0.0198	96.70 ± 0.0003
Cost sensitive			
ADTree	93.27 ± 0.0048	84.13 ± 0.0131	92.41 ± 0.0038
BayesNet	95.29 ± 0.0014	85.44 ± 0.0234	94.37 ± 0.0014
Logistic	95.81 ± 0.0005	82.13 ± 0.0168	94.53 ± 0.0005
SMO	94.85 ± 0.0004	86.56 ± 0.0076	94.07 ± 0.0004

3. Results

3.1. *Acceptance of the method*

The results of the questionnaire carried out by the users are presented in Table 4. The most striking result is the rating of transcriptionist-oriented systems approach: even though it is the most widespread approach, it has the smallest rating of −15. The results for RTTOS, telephone access, DBSR are more or less similar to each other with a rating of about −5 out of 32; the rating of handwriting, −7, is slightly less than these three approaches. The rating of ASDCIAS is 1, which means that the advantages and the disadvantages almost balance each other. Overall average rating of SISDS which is 25 out of 32 seems very satisfactory.

3.2. *Usability of the method for building diagnostic decision support systems*

As mentioned in the previous section, the esophagus report contains 72 variables, 53 of which are nominal and the remaining are numeric; the number of instances is 1240. The instances in the data set have some missing values for some of the attributes due to the trigger based dynamic activation of (sub-)sections, or simply because the value was not known by the user. As the target diagnoses, we focused on the three significant ICD-10 codes, i.e. K21.9, K44.9 and K22.4; the observation rates of other diagnoses were low that make them infeasible for further study. Our web-based prototype has the capability to export the collected data in a format that can be directly imported by the machine learning tool that we used, i.e. WEKA, so that different algorithms can be tested with ease and a decision support system can be developed rapidly.

After importing the collected esophagus data to WEKA and applying a conjunctive rule learner using K21.9 and K44.9 diagnoses as target classes, we found out that both of them can be predicted with a high accuracy (98% and 98.8%, respectively) depending on the answers of two particular main data entries. Therefore, we opted for the non-trivial case of K22.4 as our target diagnosis, in which the prediction rate of the conjunctive rule learner is low (71.6%) for the patients having the corresponding health problem. The diagnosis of K22.4 appears in all age intervals and sexes, most notably common for older people and female sexes (Fig. 7a).

We first applied the algorithms on the data set without any additional processing steps (Table 5). The overall prediction rates were high for all classifiers (>93.5%) and the support vector machine had the best accuracy rate of 96.7%. However, the correct prediction rate for patients with K22.4 diagnosis were low (<78.4%). It is easy to observe that the number of instances without K22.4 diagnosis in the data set is much larger than those with the K22.4 diagnosis with a ratio of over 1/10. This high ratio means that the data set is unbalanced and prone to bias in the class-wise classification results. In order to remedy this situation, which emerges as a common feature of most diagnostic related medical data sets, we applied cost-sensitive classification. In cost-sensitive classification, classes have different costs associated with them; the classes with less number of instances are assigned higher costs to reduce the number of false predictions, and consequently increase the accuracy for that class. In our experiments, we tested several cost matrices and the best results have been obtained by a cost matrix that assigns a weight of 10.0 to instances with K22.4 diagnosis and 1.0 otherwise. This leads to a significant increase in prediction accuracy of the patients with K22.4 diagnosis for all classifiers (almost 30% increase for the BayesNet and $\approx$ 8% for the others) despite a small loss of 2–4.9% in the correct prediction rate for the healthy patients (in the sense that having the K22.4 diagnosis). The prediction accuracies that we obtain in the experiments show that a successful diagnostic decision support system can be built on top of the esophagus data collected by the SISDS method.[7] In addition, since we are making use of existing off-the-shelf components, the effort required to create the system is also low. In our particular case, WEKA provides a library to load trained classifiers, run them over new instances and retrieve the predictions, which was easy to integrate into our prototype.[8]

3.3. *Reliability and the performance of the method*

In terms of time: in transcriptionist-oriented approach, 10 reports were recorded independently by 8 radiologists nonstop as speech; the total length of recordings from the beginning to the end is 880 min. The entire process took that much time to complete, averaging 11 min data recording time per case. However, the recordings still need to be transcribed in machine readable format by transcriptionists and then approved by the radiologists before they become ready to use. This consequently delays the dissemination of the reports. The length of this process depends on the number of available transcriptionists. In our case, there were four transcriptionists and they transcribed all 80 reports in 1040 min, averaging 13 min per report, in machine readable format. Approving the reports by checking their contents took another 412 min (averaging 4 min per report by a radiologist). This corresponds to a total time 2332 min, averaging 29 min per report assuming that there are no delays between the stages of recording, transcribing and approving it.[9] 7 reports among 80 transcribed reports were corrected by radiologists. When we compared the contents of the approved reports and the recordings, we identified differences in 12 of them. Although the differences were not fatal, this still shows that the process is prone to errors in spite of the extra transcriptionist cost. In the SISDS approach, the reports were stored in the database in a machine readable and structured format in a total time of 1120 min and ready to be disseminated, averaging 14 min data input time per case. Note that, each report immediately becomes available for further use as there are no other steps involved.

In terms of diagnosis success: with transcriptionist-oriented approach, only 2 out of 8 radiologists diagnosed both of the two K22.4 cases correctly, 3 radiologists diagnosed one of the cases, that is the overall success rate of diagnosis is 43.75% (7 out of 16). On the other hand, for the SISDS methodology, 6 radiologists diagnosed 2 of the K22.4 diagnoses in 10 cases correctly, 1 expert diagnosed just 1 of them correctly, that is, only 3 cases through all cases with K22.4 were not diagnosed correctly out of 16 cases resulting in a success rate of 81.25%. Note that the difference is quite significant, and the SISDS approach seems to be successful in guiding professionals during the diagnosing process.

4. Discussions

There exists a wide range of data collection methods in medical reporting. Users who wish to place a priority on minimizing the time required for the capture of data usually prefer non-structural methods. On the contrary, users who place a priority on improving the efficiency of reviewing or analyzing the information have gravitated towards structured information capture methods. Similarly, users who place a priority on improving the quality and efficiency of patient care by using more effective workflow processes have increasingly moved towards interactive methods; interactive recording is a more complex version of structured reporting as it interactively prompts and provides feedback to the person using it [8].

The methodology that we propose is aimed to serve promptly to all of the users with different priorities. The SISDS method aims to cover the different needs of all the actors in the field, whereas current prominent approaches mostly attach importance to the priorities of a very limited number of actors, usually laboratory professionals who aim to generate the highest number of medical reports each time. Furthermore, most of them, in particular the structured ones are customized for specific fields (e.g. BIRADS [25]). Although they are created in the hopes of addressing well-documented deficiencies in report content and organization, they largely failed in its adoption due to concerns over workflow and productivity [2]. The presented method brings a new understanding for writing or displaying generated reports from the point of view of both their writers and readers. It is possible for physicians to see reports generated by laboratory professionals either in a free-text form or in a structured nested hierarchical form in which abnormal conditions are highlighted to draw their attention to these sections. Furthermore, as several sources point out, in most cases medical reports belong to normal cases in which there are only few fields with abnormal values depending on the case under examination.[10] Ideally, regardless of the priority, much less time has to be spent to record normality, and for the sake of cognitive simplicity the user

[7] See [3] for additional results.

[8] The time consuming part was analyzing the data to choose the algorithms that perform well, which took about two days in this case study.

[9] In our case, transcribing the recordings was a batch process and the transcriptions were not available for approval until all recordings were processed by the transcriptionists; this corresponds to an additional delay of about 6 h.

[10] This fact has been observed in our study as well: 57.8% of 1240 esophagus reports belongs to healthy patients including no abnormal values; 42.4% of them includes only few fields with abnormal values, very limited when compared to whole abnormal values defined in the format of the esophagus report.

should not receive data entries related to abnormal situations; the SISDS method achieves this by conducting a simulated walk on the necessary steps using the default values for the normal cases in order to generate an initial report template. The method also enables clinicians to consult other colleagues in their native language by transforming the report into other languages instantly as is in an error-free way.

The real world performance of the SISDS approach has been tested with the prototype implementation put into practice at several radiology departments. The questionnaire applied to the user to evaluate the acceptance of the SISDS have a remarkable result. The overall average rating of SISDS by medical professionals in comparison to other most common approaches based on the conducted survey seems highly satisfactory (25 points out of a possible maximum value of 32). Apart from a very limited number of 20 professionals that answered the questionnaire, it is clear from these results that health care professionals are not satisfied with the current approaches, especially with the most widespread approach of transcriptionist-oriented systems that has the lowest rating of −15, and they seem to be eager to migrate from the existing approaches to a more satisfactory approach, such as the one we propose. The quantitative results of the applied testbed of the SISDS method and the feedbacks that we received from the users who evaluated SISDS alongside with other existing methods prove that the proposed method is more effective in many perspectives, such as facilitating a complete and accurate data collection process and providing opportunities to build decision support systems without tedious pre-processing and data preparation steps. The diagnostic decision support system base on the collected data has been built using off-the-shelf tools and it proves its success in guiding professionals during the diagnosing process with a success rate of 81.25%; the success rate is 43.75% for the most widespread transcriptionist-oriented systems approach. SISDS mainly helps health care professionals practice better medicine by reducing the turn around time to disseminate medical reports. Despite these encouraging result, we would like to underline that our study includes very limited number of target diagnosis and the data set is of moderate size (about 1300 instances). Moreover, in the SISDS methodology, users that have to return to the computer screen while generating reports are still, to some extent, faced with a look-away problem, although, this problem is reduced in the SISDS methodology as a considerable part of the medical report is generated by the system. A possible improvement to ease the look-away problem would be to integrate a speech interface into the SISDS method that guides professionals through medical reporting using text-to-speech and enables them to change the values of the data fields using speech-to-text. Speech recognition has been reported to decrease productivity largely due to additional time requirements associated with report editing [2,26,27] and more errors when compared to transcriptionist-oriented systems [28,29]. However, since data fields are well-defined in the SISDS approach, the context of the speech recognition problem will be limited and hence it may be possible to attain higher recognition accuracy.

Another issue we would like to share is that the standard coding systems upon which professionals or institutions agreed on are very limited. In our condition, despite the fact that the essential part of the sample esophagus report is based on a well-known reference [20], the radiologists had different insights about the details of the report and hence reaching a consensus turned out to be a non-trivial task. There is a lack of standards and a lack of consensus on proposed standards in medicine. If the process of knowledge-base construction is highly dependent on a single individual or sample data, or carried out only at a single institution, then the survival of that system over time is in jeopardy; setting a standardized terminology would help healthcare providers to have complete and easily accessible information about patients that would result in better healthcare [7,30]. Without agreeing upon a standard coding system, healthcare professionals are inclined to generate medical reports in free text form. Designing new domain sets for specific areas should be carried out by international and national organization as well as by the leadership of the governmental offices to provide a consensus among institutions and professionals. Furthermore, acceptance of a system will not be guaranteed even if a system performs as intended. Social, cultural, behavioral and financial issues together with many other challenges have as much to do with the success or failure of a system as do technological aspects [2,4,31]. We acknowledge that there are barriers for the acceptance of a new method to be integrated into a complex organizational environment such as hospital information systems (HIS), laboratory systems, or a part of Picture Archiving and Communication Systems (PACS). The adoption of standardized documentation techniques that reduce medical errors and benefit a system may require policies of either governmental offices or institutions, and may require incentives such as a better diagnostic performance, time efficiency, extra payment or benefits to induce professionals to switch from traditional information capture methods to methods that are more interoperable, economic, and provide a basis for better care.

5. Conclusions

In this study we propose a new methodology which adopts a systematic approach to improve medical reporting process by reducing variability and minimizing errors. More specifically, we focus on the process of data entry and report generation. The interactivity with a versatile, user and problem driven, scalable and dynamic reporting system is the proposed solution to avoid inefficiency, cognitive load and medical errors. These together with a free-text like inline data entry have many advantages that allow information to be captured at the point of care and eliminate the need for a transcriptionist or auxiliary procedures to write reports. In particular, the end report is automatically generated while structured fields are filled interactively in a natural form; it also provides

1. a high degree of timeliness and accuracy, reducing errors,
2. multifunctional capabilities such as drawing the attention of practitioner to important sections of the report, alerting him about a diagnosis or giving advises at the time of entry, and
3. an easy way for domain experts to define reports in a textual form without extensive computer knowledge.

The initial feedback that we received from the users of the implemented prototype and the evaluation results indicate that the proposed method is a promising approach for achieving the aim of effective data collection and reporting, preferable to the existing approaches. It also provides a proof-of-concept that similar studies can be conducted and diagnostic decision support systems can be developed rapidly for other (medical) domains by incorporating SISDS with off-the-shelf solutions; with appropriate choices, such as adding cost-sensitivity, remarkable results can be obtained. Further studies will concentrate on a wide-scale deployment of the system, and development and integration of a more complete medical decision support system based on the collected data.

Summary points

What was already known on this topic:

- There has been an increasing demand for high quality medical data in a standard electronic format that can be easily shared and used later for various purposes (such as, statistical analysis or in decision support systems) without extensive post-processing.
- This need has been brought forward by many studies and some customized methodologies for specific areas have been proposed.
- Existing approaches have certain shortcomings and seem inadequate for collecting accurate and high quality data with ease. In particular, the conflict between cognitive load and structured data entry does not seem to be resolved.

What this study added to our knowledge:

- This study proposes a new methodology, namely SISDS, in medical reporting.
- The results of the study indicate that medical reports can be generated more effectively and efficiently with the approach proposed.
- More robust diagnostic decision support system can be established easily with off-the-shelf tools in term of the improved quality of the data collected during reporting with the approach.
- The proposed methodology rather than some customized methodologies for specific areas can be implemented in a broader number of medical fields.

Author contributions

Dr. Kemal Arda brought forward the needs and the lacks in the area. He leaded all the study from beginning to the end. He sometimes consulted with other radiologists and clinicians from several institutions and asked for their cooperation especially during both data collection and testing the methodology. Moreover he organized and managed the manuscript to be produced. The study couldn't be realized without his leadership.

Dr. Kaya Kuru did most of the research about what was already known on this topic and what should be done to improve the current studies. The first and the second preliminary versions of the methodology were established by him. Later, the last improved and successfully tested version of the methodology was developed by collaboration between Kuru and Dr. Sertan Girgin. Girgin contributed very much while establishing the infrastructure to remove the shortcomings of the first and the second versions in terms of establishing the objectives in the study, especially for the establishment of the decision support section of the study. Kuru, together with Dr. Ugur Bozlar, visited and interviewed with the medical professionals at the other institutions to get their contributions to the study. Bozlar gave great effort during data collection phase. The first draft of the manuscript was formed by Kuru. Girgin, Arda and Bozlar contributed greatly to generate the final manuscript.

Conflict of interest

There is no conflict of interest.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ijmedinf.2012.05.019.

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