Information and Communication Technology for Process Management in Healthcare: a Contribution to Change the Culture of Blame

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Abstract. Statistics on medical errors and their consequences has astonished, during last years, both healthcare professionals and ordinary people. Mass-media are more and more sensitive to medical malpractice. This paper elaborates on the well-known resistance of the medical world to disclose actions and processes that could have caused some damages; it illustrates the possible causes of medical errors and, for some of them, it suggests solutions based on information and communication technology. In particular, careflow management systems and process mining techniques are proposed as a mean to improve the healthcare delivery process: the former by facilitating task assignments and resource management, the latter by discovering not only individuals’ errors, but also chains of responsibilities concurring to produce errors in a complex patient’s pathway. Both supervised and unsupervised process mining will be addressed. The former compares real processes with a known process model (e.g. a clinical practice guideline or a medical protocol), while the latter mines processes from raw data, without imposing any model. Potentiality of these techniques is illustrated by means of examples from stroke patient management.

Keywords: Healthcare process management, clinical practice guidelines, careflow management systems, medical errors, risk management

1 Introduction

Historically, medical errors have been a kind of “professional secret”, something to hide for preserving the institution’s image and the individual’s credibility. A novel written in 1945 by Ben Hecht, published in [1], tells about a mysterious X Club,
composed by 14 leading medical experts in different fields. The novel starts on a senior physician, member of the club, illustrating the purpose of the club itself to a novice:

“… the members of the X Club have a single and interesting purpose in their meeting. They come together every three months to confess to some murder any of them may have committed since our last assembly. I’m referring, of course, to medical murder. Although it would be a relief to hear any of us confess to a murder performed out of passion rather than stupidity... Indeed, Dr. Warner, if you have killed a wife or polished off an uncle recently, and would care to unbosom yourself, we will listen you respectfully. It is understood that nothing you say will be brought to the attention of the police or the A.M.A. ¹ … we are not here to ease our souls but to improve them. Our real purpose is scientific. Since we dare not admit our mistakes to the public and since we are too great and learned to be criticized by the untutored laity … we have formed this society. It is the only medical organization in the world where the members boast only of their mistakes. … allow me to define what we consider a real, fine professional murder. It is the killing of a human being who has trustingly placed himself in a doctor’s hands. Mind you, the death of a patient does not in itself spell murder. We are concerned only with those cases in which a doctor by a wrong diagnosis or by demonstrably wrong medication or operative procedure has killed off a patient who, without the aforesaid doctor’s attention, would have continued to live and prosper”.

The story continues with the novice confessing his last mistake and, at the end of the story, the fifteen doctors save a human life by solving an extremely difficult diagnostic problem, exploiting previous reasoning about their “murders”.

This novel rises this observation: sharing error experience was perceived as a need among “good” physicians, even when the culture of blame was dominating; while “learning from errors” seems a quite new motto, it is not a recent paradigm (the novel dates more than sixty years ago).

In the last years, something is changing in the medical culture indeed. X Club’s-like clinical cases are no more confined to a “professional secret”, they are more and more source of statistics, they are reported by mass-media, and published in the scientific literature.

Healthcare organisations are changing their view, probably for two concomitant causes: on one hand, people is more and more informed due to the high diffusion of communication facilities (mainly the internet), so that it becomes difficult to hide errors, or to confine the story to a limited environment; on the other hand, healthcare

¹ American Medical Association
organisations understood that reducing errors is *convenient*, not only for the population’s health, but also for reducing healthcare costs, so improving efficiency. Thus, while both scientific literature and mass-media are more and more sensitive to the problem [2-6], “risk management” is becoming a must in every healthcare organization.

We are still far from a definite solution because, as well shown within an interesting discussion in the literature [7,8], "changing the culture of blame requires a revolution". Nevertheless, as medical informatics researchers, we can foster this process, and this paper shows how Information and Communication Technology (ICT) may be applied to risk and errors management.

In order to tackle the problem and propose methodologies and technologies for reducing medical errors, we must go from the level of statistics and generic complaint to the individual process level, to understand how and why errors happen. This is not (only) for blaming one or more individuals, but for reconstructing the pattern of actions that led up to the error. Opposite to the first impression, often this procedure relieves the individual, by discovering a chain of responsibilities.

In the next sections, nature of medical errors is discussed, and some solutions are proposed.

### 2 Medical errors and need for documentation

Everybody is concerned with medical errors. Patients are more and more informed and ask for medical excellence; healthcare personnel is more and more worried about increasing complaints; healthcare administrators are worried about waste of resources and increasing insurance fees. Insurances themselves have started modulating their fees according to the error prevention actions of their clients. As an example, the Hospital San Martino in Genova, Italy, has started using a novel technology for increasing the safety of drug administration, combining an automated drug-cabinet and a patient-tailored unitary dose preparation: this risk-reduction initiative let them save 2 million Euros on the insurance fee. As a matter of fact, the fee decreased from 40‰ to 26.3‰ of the gross personnel income, which is the amount of money on which insurances normally base their fee calculation. This means that safety-oriented process re-engineering is becoming a *must* in healthcare organisations.

In order to propose ICT-based solutions, it is necessary to understand the nature and the cause of errors, and to clarify what the word "error" means. There are events that everybody should define "errors", e.g.: administering a wrong drug because of similar, confounding drug packaging; wrong interpretation of bad-calligraphy prescription; misunderstanding a diagnostic test. These errors, illustrated in Figure 1, are caused by distraction, ignorance, superficiality; also mental fatigue is a common cause: for example,
Sensitivity of mammography is correlated to radiologist’s tiredness, and in fact it may be improved by computer-assisted diagnosis, as shown in [9]. These kinds of errors are (often) easily recognised because they cause a specific adverse event.

There are several statistics in the literature about these errors. For example Holloway et al [10] analyzed errors and adverse events, within a voluntary and mandatory event reporting system, in 1,440 stroke patients over a 3.5-year period. Of the admitted during the study period, 173 patients experienced an adverse event. About half of them were caused by preventable errors: 37% were transcription/documentation errors, 23% were failure to perform a clinical task, 10% were communication/handoff errors between providers, and 10% were failed independent checks/calculations. Statistics, as in this case, often come from a research study. Of course they are useful, because they highlight a situation that is often unknown, or at least not clear enough, to the healthcare personnel. But they would be much more useful if they were collected continuously, as part of the clinical routine. First, they would allow to understand “where” to concentrate error prevention efforts: if transcription errors are a problem, this will foster adoption of electronic clinical charts; if failure to perform a clinical task is common, this will foster adoption of clinical practice guidelines (GLs) and protocols, and so on. Second, when collected on a regular basis, they allow verifying whether corrective actions are effective.

Temporal trends may be shown by means of graphs such as those in Figure 2. Documenting the effect of an intervention is recommended to enforce and motivate behaviour change of healthcare operators.

Behaviors described above are very easy to be defined as errors. But there is a more subtle definition of error, referring to non-compliances with GLs and protocols [11]: can they be considered as errors? Sometime the answer is straightforward, when they directly cause a “visible” damage (leading to patient/relatives claim, legal actions, etc.). But more often it is difficult to judge, because they do not cause such damage and/or they can be justified as due to exceptions. In fact, every patient is a specific case, and may need to be treated as an exception with respect to a GL. However, there are scientific studies showing that GL compliance improves the outcome. For example it has been shown that stroke patients benefit from GL application [12]. Looking at survival curves, patients whose treatment includes more than five non-compliances show a 15% survival decrease at six months, with respect to those treated with higher GL compliance. Probably, none of the additional deaths is due a very specific error, but we can say that “better the process, better the survival”. Therefore, even if non-compliance cannot be straight defined as an error, it should be worth to pretend a motivation for it. In this way, very important documentation can be collected, that becomes both a justification and a basis for further statistics. As a matter of fact, a healthcare organization must monitor its
outcomes (health, economic, etc.) and correlate them to processes, in order to show, by means of objective measures, that some processes are better than others [13].

3 Discovering what’s wrong in a process

Healthcare processes are very complex and of very different nature. We may distinguish (the list is not exhaustive):

- Patient management
- Communication among healthcare professionals
- Communication between professionals and patients
- Healthcare personnel (human resources) management
- Patients pathways
- Non-human resource acquisition and maintenance
- Education

Within this variety, it is useful to classify processes according to some attributes, in order to cope with each process class using the correct methodology for error detection.

3.1 Classification of Processes

First we distinguish “medical processes”, where medical knowledge representation and management is important, and they are diagnosis, treatment, monitoring, nursing, etc., from “organizational processes”, where resource management and synchronization are more important, and they are hospitalization procedures, emergency/rescue procedures, clinical pathways, outpatient management, etc.

Several medical processes are (should be) driven by clinical practice guidelines and/or protocols. In this case knowledge about “what to do” is explicit, practice can be compared with theory and we can talk about compliance/non-compliance with expected patterns. On the other hand, organizational processes are more driven by “oral tradition”, consolidated routine, and so on. In this case, knowledge about “what to do” is tacit and the process cannot be compared with a gold standard. The reader is referred to [14] for a deep insight on explicit and tacit knowledge and knowledge conversion processes. This distinction between explicit and tacit knowledge, underlying different processes, will be recovered in section 3.3 addressing process mining techniques.

Another classification axis is time. There are short-term processes, such as those occurring during hospitalisation, outpatient visit reservation and delivery, and ticket
payment; there are long-term processes, such as life-long treatments, whose outcomes are only measurable in terms of patients’ survival and quality of life. Also economic investments and attempts to balance expenditures with DRG reimbursements are long-term processes, because they imply monitoring costs and benefits for long time. Time-based classification is necessary in order to assess the scheduling of measurements for error detection and corrective actions efficacy, i.e. the time scale of Figure 2.

3.2 Action-related and Process-related errors

Several people and resources are involved in a process, and errors may occur everywhere. There are action-related errors, i.e. errors with a well-defined cause, occurring during a specific task of the process, but several ones are process-related, and in this case it is much more difficult to individuate responsibilities.

As an example of process-related malpractice, let us consider the omission of thrombolisis, a very effective acute-stroke treatment that unfortunately is performed in a very small portion of eligible patients [15]. As a matter of fact, it must be performed within three hours from the stroke symptom onset. If a patient does not arrive on time at the emergency department or, while being arrived on time, he stands more than three hours waiting for the neurological imaging (a mandatory test before thrombolisis can be administered) or for the specialist visit, who is responsible? Here, the process involves patient himself, his relatives, the general practitioner (GP), the transportation to the hospital, the emergency department, the radiology department and the stroke unit. Delays may occur in each of these steps: patient, his relatives, and GP could underestimate the symptoms, the transportation service may be inefficient, the radiology department could be overbooked, the neurologist may be unavailable at that moment, and so on.

To discover where the bottleneck has been in a specific case, and whether there are systematic bottlenecks in the process, due to a chronic lack of resources or skill, we must keep track of the process: this can be done only by collecting the process data and analyzing them with opportune techniques, such as those described in the following sections.

3.3 Process Mining

There are multiple ways of collecting information on medical errors. The most common rely on voluntary provided information: questionnaires are administered to physicians and nurses in anonymous form to elicitate their “feeling of risk” [16,17], and also to patients to know their perception of errors [18,19]. Recently, tools for electronic data collection have been developed [20]. These initiatives are very important to change the shame and blame culture, mainly when the survey results are periodically discussed.
together with all the team components, and corrective actions are planned through a consensus process. However, voluntary-reported data could be poorly reliable: willing to disclose opinions and feelings is highly correlated to the atmosphere of the working setting, and response rate may be highly variable. For these reasons, more objective measures are necessary and they can be obtained only by analyzing real processes by means of real data.

The term “process mining” refers to a set of techniques able to infer process models from raw data, namely the “event logs” [21,22], which may originate from running systems, such as electronic clinical chart, decision support systems, etc. recording sequential actions. Possible outcomes of process mining are:
- action flows, showing the most common patterns of actions that occur in a business process (in section 3.3.3, action flows derived from real-world data will be shown);
- Petri nets, that also represent action patterns, but in addition can be used for individuating bottlenecks, as far as waiting times from an action to another (transition times) are represented; they also can be used for simulation purposes, for example to test the system under a different resource assignment;
- Social networks, showing relationships among agents and actions

In the next sections, we distinguish between supervised and unsupervised process mining, depending on the knowledge underlying processes. As mentioned before, this knowledge can be explicit or tacit so that we can have a gold standard to be compared with real process or not, respectively. In any case, real process may be different from the expected behaviors and real outcomes different from expected ones. Our purpose is to detect this gap and find an explanation for it, if possible.

Since raw data are at the basis of any process mining, let us start by defining “process data” and their collection.

3.3.1 Process data and careflow management systems

More and more tools based on ICT are being used by healthcare organizations and thus more and more data are collected and shared within and among organizations. But what makes a data item a “process data”, suitable to generate enough informative event logs? Consider, as an example, the blood pressure. The simple numbers (e.g. 140/85 mmHg) are not process data. But they become process data as far as we know:
- When blood pressure has been measured
- When it has been stored
- Who measured it
- Who stored it
Current technologies allow enriching a data item with this kind of information. For example, if the electronic medical record is part of a workflow management system, that in this case is called careflow management system (CfMS) [23], a lot of process information is stored automatically: the system user is identified through the login data, the timing may be captured through the system clock, the resource utilization may be inferred by the organizational model represented in the CfMS, and so on. In fact, a CfMS embeds both medical and organizational knowledge. In general, medical knowledge implements guidelines and/or protocols recommendations, encoded as logical rules. Organizational knowledge is used to assign tasks to the different “system agents”, i.e. physicians, nurses, etc., according to the skill necessary for that task; moreover, organizational knowledge allows the system to choose among similar tasks, according to the current availability of resources.

From the user’s point of view, using a CfMS is not very different than using a simple electronic clinical chart. Several functionalities make the difference but are “transparent” to the user. For example, the list of data forms to be filled is both user- and patient-tailored, and it changes automatically over time, according to urgencies. Alerts and reminds take into account the skills of the logged user. Messages are automatically sent to the opportune roles, according to the message content or to the sending role. Every system access is stored together with its time-stamp and login information.

It is clear that a CfMS allows a better documentation of processes with respect to a simple electronic clinical chart.

### 3.3.2 Supervised process mining

Supervised process mining implies explicit knowledge of processes to be available. As an example, the system implemented at the Stroke Unit of the Mondino Hospital in Pavia is described. A CfMS, based on recommendations of the Italian stroke management guideline SPREAD [24] has been implemented. It manages the execution of the care process for each patient, verifying the GL rules, generating specific recommendations, and communicating recommendations to the opportune role (physician, nurse, etc).

One important ancillary tool of the CfMS is RoMA (Reasoning on Medical Actions), triggered by the patient’s discharge [25]. It analyses the care process of a patient, discovering non-compliance with GL. In practice, it matches the patient’s data with the GL rules, formalized in a computer-interpretable syntax of the type “IF-THEN”. An
example of the report obtained is shown in Figure 3. The report is composed by three sections: the first one refers to lack of important data (“yellow” is the color of near-mandatory data input fields in the user interface). Without “yellow” data, the system is not able to complete the GL compliance check. The second section illustrates all the recommendations the patient is eligible for. The third one shows the non-compliances. To the purpose of error management, the RoMA tool is the most interesting part of the CfMS. In fact, it allows reasoning about the specific case, noticing what has been omitted and which actions could deserve attention, having a certain probability of being incorrect. Remember every patient is a unique case, thus there could be justifications for actions that are not included by the GL; the physician may insert the motivation for non-compliance, choosing from a taxonomy, shown in Table 1, and/or inserting comments in free text format. Systematic collection of these motivations is a means to continuously improve the GL implementation and the GL versioning. A regular users’ feedback allows creating a “community of practice” [26]:

- at a local level, once non-compliances have been labeled according to the taxonomy, reports are produced and sent to persons, hopefully able to tackle the problem: a recurrent “out of work” of an instrument will be notified to the clinical engineer; frequently missed data will be notified to the EDP department; frequent errors could call for an educational initiative from the hospital direction, and so on.

- at a higher level, more interestingly, frequent disagreement on a recommendation is communicated to the scientific board that is in charge of the GL update: may be that recommendation is not suitable for all the implementation sites (it may require resources that are not always available) or, if non-compliance is uniformly distributed among hospitals, probably there is new evidence from scientific studies that makes the recommendation obsolete.

If this reporting procedure becomes part of the clinical routine (i.e. the RoMA tool is regularly activated at every patient’s discharge), probably physicians will be more willing to share experiences and also to admit their mistakes, when their justifications, after discussion, are shown to be too weak. For example, two unexpected behaviors detected by RoMA are related to the administration of antiplatelet agents for secondary stroke prevention: although the low cost and easy administration modality, these drugs were prescribed only to 61% of eligible patients. Similarly, deep venous thrombosis prevention was performed only in 56% of cases. After these observations, a reminder system was implemented and percentages increased to 76% and 92%, respectively.

The consciousness of being part of a “community of practice”, where an individual can contribute to the improvement of a product (the GL in this case), is likely to encourage the individual to disclose a possible incorrect behaviour.
### 3.3.3 Unsupervised process mining

Unsupervised process mining is useful when:
- there is no explicit knowledge available about certain processes, and we want to describe these processes for further investigations.
- it is necessary to compare processes among different organizations, for example to check whether similar patients are managed homogeneously or not, or whether management costs are different.

In these cases, process mining algorithms allow do discover several aspects of a workflow starting just from event logs, capturing patients and physicians’ behavior previously unknown. It is possible to learn social networks, individuate bottlenecks and pitfalls, create Petri nets for simulation purposes, and reconstruct process flow. In general, we can discover earlier some process anomalies and prompt for corrections.

As an example, results from data about stroke management in two Italian hospitals are shown. They were obtained by using ProM [27], a tool developed at the Technical University of Eindhoven.

Figure 4 shows the first part (the first actions after the patients’ admission) of the processes mined for the two hospitals. It is very clear that the two hospitals adopt different strategies: on the left, immediately after the admission, specific treatments for stroke are administered, while, on the right, physicians prefer starting with treatment of stroke complications rather than stroke causes (that will be treated later, not shown in the figure). Different "schools" have been discovered, that underline the treatment of similar patients. Of course, different processes could lead to different outcomes, and comparisons may be produced to the medical community for further reasoning.

### 4. Conclusion

Among other ICT tools, medical informatics community must promote careflow management systems and process mining techniques, showing their potential to reduce the clinical risk by improving healthcare processes. This will encourage healthcare administrators to adopt these tools and physicians to use them.

Still some obstacles remain to the full exploitation of such techniques. From our experience, one big problem is to manage interconnected healthcare systems (for stroke care they are emergency room, acute ward, rehabilitation units, and home care settings), because this requires an agreement on ICT tools among different institutions, and this is difficult to be achieved. However, the current trend of National Healthcare Systems is toward integration, thus we are confident that common and sharable data repositories will be available in the future, and exploitable for process management. In Italy, there are
examples at a Regional level: the CRS-SISS system (Regional Card for Services- Socio-Health Integrated System) in the Lombardia Region is now implemented, and every citizen’s access to a public service is stored centrally. Now the problem is that most of data are still unstructured, thus the next step is to switch from unstructured to structured data, to allow a more focused data retrieval.

We are aware that several technical, organizational and political issues must be faced, but the good sign is that regional and national administrators start showing a great interest in process management techniques. More or less explicitly, this represents a trend toward transparency, including disclosure of tacit, often incorrect, behaviours. This is a great opportunity for medical informatics community to experiment research products on real data, making them quickly available for deployment.

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Figure captions

Figure 1 - From top left to bottom left: bad calligraphy for prescriptions, in receipts and on the drug package; instrument forgotten inside the body during surgery; similar packaging for different drugs, facilitating drug confounding; identification procedures, still too rare in hospitals; too many examinations per day cause physicians’ attention to decline at the end of the day.

Figure 2 – Graphical representation of the efficacy of an intervention on the number of errors. Different situations may occur: the number of errors declines rapidly from a constant level to a lower constant level; the errors, that already were decreasing, decrease with a higher slope; both level and slope improve.

Figure 3 – The report of the RoMA tool: lack of important data, recommendations for which the patient is eligible, and non-compliances.

Table captions

Table 1 – Motivations for non-compliance: physicians may choose a motivation from the list or insert a free comment.
Figure 2
### RoMA - Patient Report

#### MARIO ROSSI FINAL REPORT

#### (a) LACK OF YELLOW DATA

<table>
<thead>
<tr>
<th>Category</th>
<th>Data Available</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recent History</td>
<td></td>
<td>Insert Motivation</td>
</tr>
<tr>
<td>Neurosonologic Examination</td>
<td></td>
<td>Insert Motivation</td>
</tr>
<tr>
<td>Cardiologic Diagnosis</td>
<td></td>
<td>Insert Motivation</td>
</tr>
<tr>
<td>Physician Diary</td>
<td></td>
<td>Insert Motivation</td>
</tr>
<tr>
<td>Objective Examination</td>
<td></td>
<td>Insert Motivation</td>
</tr>
<tr>
<td>Vital Signs</td>
<td></td>
<td>Insert Motivation</td>
</tr>
</tbody>
</table>

#### (b) THE PATIENT WAS ELIGIBLE FOR:

- **R1.5 (A)** Aspirin (160-300 mg per day) is recommended in all patients with acute stroke unless anticoagulant therapy or thrombolysis are indicated.

- **R1.15 (A)** In patients with stroke secondary to atherothrombosis of extracranial vessels who were not on antithrombotic therapy, aspirin (160-300 mg per day) is the recommended treatment.

- **R1.19 (B)** In patients at high risk of deep venous thrombosis (DVT) (i.e., presenting with plegic limbs, or reduced consciousness, or obesity or previous lower-limb venous diseases) prophylaxis with subcutaneous low-dose heparin (2000 IU, twice daily) or low-molecular-weight heparin is recommended starting since hospital admission.

#### (c) GL NON-COMPLIANCES

- **R1.18 (B)** Patient with plegic limbs.
Table I

| 1. Organisational Problems | 1.1 Lack of personnel  
|                          | 1.2 Lack of non-human resources (Instrumentation / Drugs)  
|                          | 1.3 Data/Information flow problems (e.g. difficult communication)  
| 2. Technical Problems     | 2.1 Instrumentation fault  
|                          | 2.2 Software bugs/malfunctioning (causing errors in data interpretation)  
| 3. User-related issues    | 3.1 Disagreement with the guideline  
|                          | 3.2 Participation in a Research Protocol (justifying deviation from guidelines for research purposes)  
|                          | 3.3 Lack of adequate skill  
|                          | 3.4 Medical error  
| 4. Patient-related issues | 4.1 Lack of consensus  
|                          | 4.2 Unpredictable patient's finding making the guideline no longer appropriate  
|                          | 4.3 Early patient discharge (including death)  |