Chapter 5
Error Recovery in the Wilderness of ICU

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Introduction

Our previous investigations of error detection and correction in a laboratory setting (in-vitro) using error-embedded tasks show that individual physicians identified less than 50 % of the errors [1]. Experts corrected the errors as soon as they detected them and were better able to detect errors requiring integration of multiple elements in the case. Residents were more cautious in making decisions showing a slower error recovery pattern, and the detected errors were more procedural in nature with specific patient outcomes. In this study, error detection and correction are shown to be dependent on expertise, and on the nature of the everyday tasks of the clinicians, given that experts make top level decisions, while residents take care of patient-related problems on day-to-day basis.

Given that clinical decisions in healthcare are made in teams, this research was extended to a semi-naturalistic environment where clinical teams were given

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error-embedded cases during clinical rounds in a hospital critical care setting (Chap. 4). An attending physician presented two cases for the team to evaluate during rounds, following the error-embedded paradigm. Although the environment was naturalistic, the nature of the task was controlled, similar to the task in the laboratory condition. The study showed that more errors were identified and corrected during team interaction than in an individual condition, where team interaction facilitated error checks. However, as interaction continued, additional new errors were generated and some of which were not corrected, propagating to the level of patient care. Therefore, although the teams provided additional error checks, there was a danger of new errors going unchecked unless the team discussions were monitored.

Given the strengths and limitations of the in-vitro and semi-naturalistic studies, we decided to conduct a naturalistic (in-vivo) pilot study to investigate team decision-making and the nature of error management in a medical intensive care environment (MICU). We were opportunistic in that we used part of data that was being collected at the bedside for another purpose [2]. We used data from team interactions at the bedside that was recorded during three clinical rounds, and was analyzed using qualitative protocol analysis along with conversational analysis, including qualitative and descriptive analysis of transcript contents. The purpose of this study was to see the kinds of constraints the natural ICU environment imposed on error detection and correction, as compared to the other two experimental settings. Please note that the terms *error correction* and *error recovery* are used interchangeably in this manuscript.

Decision-Making in Naturalistic Environments

In contrast to the previous studies, in which experimental conditions were manipulated in order to investigate the process of error recovery, we discuss the paradigm of error recovery within the context of naturalistic decision-making [3]. This work is informed by the perspective that factors such as high workload, stress, fatigue and weak team coordination can contribute to human error [4], necessitating more complex explanations than provided by assigning blame for faulty decision making to a single negligent individual [5]. This perspective has shifted the priority of human error research from the study of error prevention to the study of error detection and correction [6]. In our view, the naturalistic study of the process of error detection and correction is complementary to the controlled and semi-naturalistic approaches we have presented in the previous chapters, as a means to reveal the contextual factors that influence error recovery in practice.

Current approaches in human error research in complex systems emphasize that the causes of cognitive errors that can be traced to the interaction between work context and problem solving [7]. A large body of error research has been reported in high-stress, high-risk domains such as aviation, firefighting, the military, space exploration, nuclear power, and oil and gas extraction – fields where errors would have disastrous consequences, and are exceedingly rare [8]. Researchers in the field of naturalistic decision-making (NDM), a discipline derived from cognitive science and decision-making research, have studied how experts in these complex real-world environments use their knowledge to make decisions. Decisions made in these environments can often be subject to time pressures, goal conflicts, dynamically changing conditions, and uncertain sources of information [9, 10]. As a result, decision makers in naturalistic situations tend to “satisfice,” [11] or choose a solution adequate for achieving the goal at hand under the given constraints, even if it may not be the best of all possible solutions [8].

The following is a brief summary of key principles that served as a motivation for our study. Research by Gary Klein and colleagues in the military domain found that people rely on the synthesis of their prior experiences when judging new situations [3, 12]. This synthesis of knowledge from past experiences is also known as a schema, and it “leads to the anticipation of certain types of information…then directs…behavior to seek out certain types of information and provides a way of interpreting that information” [13]. Gary Klein refers to this reliance on past experiences, or schemas, as recognition-primed decision-making, where we develop schemas that are used to evaluate a situation in view to make decisions.

Klein and colleagues found four general factors that contribute to decision errors: (1) lack of relevant knowledge (i.e., not enough experience), (2) poor information (i.e., incomplete, ambiguous, or contradictory information) or accurate information which is difficult to interpret, (3) poor projection of consequences (i.e., underestimating risk, not anticipating particular consequences), and (4) goal conflicts (i.e., pressure to meet organizational and social goals taking priority over safety goals). Research in various domains and disciplines has confirmed that when operating under stress, people make more errors on a wide variety of tasks. This is because working memory is finite and overloading cognitive resources can lead to a less efficient performance.

Team Decision-Making in Domains Outside of Medicine

Teamwork is the process by which members of the team pursue, exchange, and synchronize information in order to decide the next steps [3]. Teamwork is important to ensure that the decisions made, and consequentially the task outcome, can be at their strongest. A study conducted by the U.S. Navy found that teams that are more effective showed more teamwork-related behaviors than less effective teams [14]. These more effective teams achieved higher scores on a technical evaluation than the less effective teams; scores on this evaluation were correlated to critical effective behaviors such as prompting other team members on what to do next, helping team members who were experiencing difficulty with the task, and making positive statements within the team. In this study, these specific behaviors were especially critical for helping other team members identify errors and make correct decisions.

Success of team decision-making has been attributed to a number of factors, including expertise of team members, nature of the task and the quality of team training [15]. Team macrocognition, or situation awareness, is another important aspect in the success of team decision-making, where macrocognitive processes appear to support collaborative team activity. For example, when a hostage situation arises and rescuing those captured requires an evacuation plan, the military forms a team of specialists with different levels of expertise and experience in the context of real field encounters. These experts, who possess knowledge of how decisions are made in the field, can organize that knowledge in the context of the situation and can formulate a plan for recovery steps [16].

Team Decision-Making in Medicine (ICU and ER)

The focus of decision-making in healthcare has shifted from individual care providers to teams of care providers. In healthcare, teams form for the purposes of providing patient care including morning rounds, consultations, and case conferences, where both the communication between team members and knowledge about team members influence the nature of decisions made by the team [17]. A crucial responsibility of the team in medical practice is to make accurate diagnoses and provide patient management plans that are consistent with the diagnoses. Effective teamwork can improve the likelihood of making accurate diagnosis and patient care plan. For example, in a medical emergency simulation study, Tschan et al. found that displaying more explicit reasoning and “talking to the room” enhanced the accuracy of diagnosis, while merely considering more information did not improve diagnoses [18]. In the natural environment, using these strategies to facilitate teamwork may contribute to correction of any errors that may be generated.

Two major factors that can substantially influence discussions on the nature of medical decisions have been identified: pre-discussing the distribution of problem-relevant information (e.g. [19]), and each team member’s awareness of the other members’ unique knowledge and talents (implicit knowledge). In a study on shared and unshared information in a three-person medical team, the shared information was immediately discussed during the team meetings, as predicted. It was also found that the team leaders repeated more clinical case information than the other team members, and over time the unshared information was repeated at an increasing rate [20]. This shows that leaders are important in fostering situation awareness between team members, where shared information is minimum.

In the ICU environment, the cognitive task is distributed across team members during decision making to reduce the cognitive load [21]. There is some shared decision making, but the rest is dependent on individual expertise of health professionals such as nurses, pharmacists, medical residents and the attending physicians (called “attendings” from now on).

In a pilot *in situ* study of expertise and team decision making by Kubose, Patel, and Jordan, the authors shadowed an attending, a resident, and a medical student in an ICU, and found that the attending detected the most errors [18] but also recovered from most errors [15]; the resident detected [13] and corrected [8] the second largest number of errors; and the student detected [8] and corrected [2] the fewest errors [22].

Most of the attending physician's decisions required expert knowledge, and the errors that were corrected were likely to have serious consequences, if unattended. The error corrected by the resident required domain knowledge as well as knowledge of some routine procedures. Student's errors corrected were mostly routine in nature. The fast pace of decision-making combined with a high level of confidence meant the mistakes were generated quickly and often. However, due to the attending's expert knowledge and ability to evaluate the situation, errors that were generated were also rapidly corrected.

Method

Study Site

The data were collected at a 16-bed "closed" adult medical intensive care unit (MICU) in a large teaching hospital in Texas that averaged over 33,000 admissions in 2010. The unit is considered "closed" as the MICU team holds the primary responsibility for the care of admitted patients [23]. The majority of admitted patients were older and from minority populations. Both paper and electronic charts were simultaneously maintained and used for patient care documentation in this unit at the time of the study.

Participants

Three clinician teams from the MICU were included in this study. Each team consisted of an attending physician, a clinical fellow, an outgoing resident, an outgoing intern, oncoming resident, oncoming intern, a respiratory therapist, a pharmacist, and patient's nurse. This is the typical composition of a clinical team participating in morning rounds.

The team on **Day 1** was composed of an attending physician, fellow, outgoing resident, outgoing intern, oncoming resident, oncoming intern, a respiratory therapist, a pharmacist, a patient's nurse and one medical student (Total participants = 10). The team on **Day 2** was composed of an attending physician, fellow, outgoing resident, outgoing intern, oncoming resident, oncoming intern, a respiratory therapist, a pharmacist, a patient's nurse and four medical students (Total participants = 13). Days 1 and 2 were consecutive day, and so, the attending, fellow, respiratory therapist, pharmacist are the same across these days. The oncoming resident and intern on Day 1 were the outgoing resident and intern on Day 2. The team on **Day 3** was a new team and included an attending physician, fellow, outgoing resident, outgoing intern, oncoming resident, oncoming intern, a respiratory therapist, a pharmacist, a patient's nurse and one medical student (Total participants = 10). A total of 26 individuals participated in the 3-day study. The team composition was reasonably consistent.

Data Collection: Morning Rounds in MICU

Data were collected during these morning rounds, where the daily patient assessment and management-planning sessions were done in the MICU. During these sessions, residents presented information on real patients at the bedside, and the clinical team discussed each patient's status, diagnosis, and management plan. Each round lasted approximately 5 h, and researchers spent 3 h per day for 3 days shadowing and observing clinician teams prior to the clinical Rounds. No instructions were given to the teams by the researchers. As mentioned earlier, the present study is the reuse of a subset of data collected as part of a larger research project [2]. Team interactions were audio-recorded and transcribed verbatim with all identifiers removed. A total of 9 h of audio-recordings of clinical rounds with 34 patients were used in our analysis. Our data-coding scheme was developed based on our laboratory-based studies, observations and from the review of the literature.

Data Coding

We used a mixed strategy to analyze the transcript data, performing a coding process using a priori codes from previous work and developing novel coding when necessary. This form of documentation enabled us to capture the nuances of interactions and speech content. As shown in our previous studies that analysis of data from audio recording, note taking, and shadowing of the physicians provide an in-depth account of the development of the clinical workflow in ICU and ER environments (e.g. [23, 24]).

In this research the audio recordings were transcribed verbatim, the transcripts were segmented into the smallest units of text, which retained semantic meaning, called "utterances" [25]. An utterance can be a single word, a phrase, or a complete sentence, as long as it is self-contained and easily understood as one unit. Breaking text down into small, meaningful units is a standard method of systematically compiling data in natural language dialogue [26].

Using ideas from the taxonomy developed by Apker et al. and modifying it using an open coding process, each clinically relevant utterance was coded for content (e.g., "management decision," "information interpretation," "information

Table 5.1 Case management coding categories for data analysis

Category	Description	Example
Information aggregation	Patient information aggregated by the presenter prior to its interpretation by the entire team; multiple instances of information aggregation possible depending on the number of ongoing medical issues in the case	"MICU day no 3, she was extubated yesterday. Her problems include altered mental status, hep C, alcoholic cirrhosis, alcoholic abuse, withdrawal, NSTGMI, GI bleed, thrombocytic leukemia, UTI stage 2 DQ ulcers."
Information interpretation	Patient information interpreted based on the evidence at hand	"Because of her size, I can pretty much guarantee to you, what's in there is probably a Bivona (Bivona® tracheostomy tube)"
Additional information	Patient information requested by individuals or teams at any stage of the discourse	"So, we're going to at least, uh, we gave her Lantus, yesterday, 10 mL?"
Management decision	Decisions made about the diagnosis or management plan of the patient	"We give erythromycin and we will discontinue that tomorrow and we will continue the rest of the antibiotics."
Information loss	1. Inaccurate recall: Recalled patient information that is inaccurate, where correct information is lost 2. Failure to follow up: Question posed by team member but never addressed in discourse 3. Incomplete aggregation: All relevant information is not discussed because it was not considered necessary at the time	1. Team member discusses patient having a history of diabetes, when the information available did not show this history 2. Team member asked if patient was passing urine but this question was never followed up 3. A case presenter omitted information, which was "relevant", for the purpose of summarizing
Inaccurate interpretation	Individual makes an assumption that isn't true; includes lack of knowledge	"…regular heart rate rhythm no murmurs…" when the patient had been in atrial fibrillation
Faulty decision-making	Most often a conceptual (not procedural) error in the process of decision-making in patient care	Admitting a patient to another unit from the ICU as an overflow when it is not permitted

aggregation") [27, 28]. Additionally, since errors in communication (including clinical content) are fundamental to our analysis, if an utterance contained or was related to an error, we categorized it as either "generated error," "corrected error," or "unresolved error." These terms are operationalized in Table 5.1. After coding 10 % of the transcripts, we expanded the taxonomy utilized by Apker and colleagues to reflect the specifics of ICU work and communication styles; the final coding taxonomy is included in Table 5.2. We provide a more detailed account of our data coding method and results in the following sections.

Table 5.2 Categories of coding for errors

Category	Description
Generated error	1. When the information uttered by a team member has something that is incorrect or doubtful;
	2. Anything that is categorized as relevant information loss, inaccurate interpretation, or faulty decision-making
Unresolved error	1. When information is missing because it was not deemed relevant at the time and therefore was not collected
	2. When a question or doubt goes unanswered and there is no way to tell what happened
	3. When information is absent
Corrected error	1. When participants themselves or someone else corrects an error
	2. When a mistake is detected and corrective actions are taken
	3. When an incorrect interpretation or decision is corrected

Data Analysis: Descriptive Statistics

Descriptive statistics were used to describe the breakdown of utterances in different case management categories. Table 5.3 provides an example of team dialogue and how utterances were coded as unresolved errors, corrected errors, or statements not containing error. Chi-square tests were used to find significant deviations from expected distributions in the data.

Data Analysis: Qualitative

The transcripts were analyzed using (1) a method of discourse analysis, in particular, a version of team conversational analysis using *utterances* as units of speech examined, and (2) semantic network relationships, generated from these utterances or concepts used in the conversation by the team. To capture the temporal order of the conversation, the schematic structure of medical knowledge hierarchy from observations to findings was used [29]. The structure, by connecting observations (utterances) to findings (relevant observations) to facets (cluster of relevant findings) generate a path of decision flow, where the flow diagram was used to identify patterns of communication [30]. Observation types were further categorized into clinician and utterance types (error generated, error corrected, or neither).

Categories of Case Management

The data was first analyzed to determine if a common pattern of case management strategies found in our previous laboratory and semi-naturalistic studies could be identified in this team study. The seven components identified to form the basic structure of case management in an in-vivo setting are given in Table 5.1.

Table 5.3 An example of coding on a part of the team interaction transcript

Type of clinician	Transcript text	Case management category	Error type
Resident	Currently, her sodium is 134, her potassium is 2.9, chloride is 93, CO_2 is 25, BUN is 7, creatinine is 0.6 which is improving to 1.8, glucose is 138, calcium 8.2, phosphorus 60, mag 1.8,	Information aggregation	N/A
Resident	I am not sure if I requested it this morning…so…we have to check the orders and see.	Information loss	Unresolved error
Attending	And her K (potassium), do you know if you replaced her K this morning?	Additional information	N/A
Resident	I don't know.	Information loss	
Fellow	The K was at 80 this morning…no, it was at 145 this morning	Information aggregation	Corrected error
Resident	I haven't written them. I don't know if that is current.	Information loss	Corrected error
Resident	The thing is I just got the labs now…. yeah, she is at a total of 120 mg of plain and she is at 3.9, at first she got 40 mg and she dropped to 2.5, then she got 80 mg, then she was coming here and now she is 2.9.	Information aggregation	Corrected error
Attending	But, we don't know if that 2.9 was while she was getting the other K.	Wrong interpretation	Corrected error
Attending	I guess we wait one more day before we call…	Management decision	N/A

Figure 5.1 represents a framework for how case management categories relate to generation of error. The flow of case management categories towards management decision is presented in Fig. 5.1.

Categories of Error and Error Correction

Errors and error corrections were judged based on recognition of errors by the team and whether or not these errors were corrected. Errors were further detected for coding based on medical expertise from an uninvolved attending physician. If the team did not correct the error, the error was considered unresolved. Complete descriptions of generated errors, unresolved errors, and corrected errors can be found in Table 5.2. Errors were then connected in temporal order in the context of the topic discussed. Utterances relevant to the case that were neither errors nor corrections were marked as "not applicable."

Table 5.3 is an example from a transcript of one bed from the third day's interaction that illustrates the coding scheme. The case management categories that do not contain errors are patient information, additional information, information

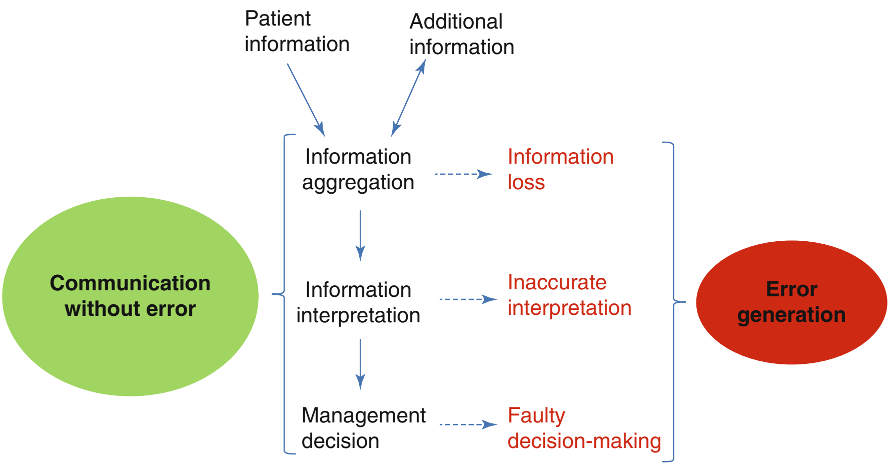

Fig. 5.1 Relationships between categories of case management and generation of errors

aggregation, information interpretation, and management decision. The categories that do contain errors are information loss, inaccurate interpretation, or faulty decision-making.

The teams have been collapsed in the following analyses to simplify the presentation of results. Additionally, since teams were made up of clinicians with different roles, to simplify presentation of data, the roles associated with the fewest utterances, including Case Manager, Intern, Nurse, Pharmacist, and Respiratory Technician, have been combined into the category "Other."

Our analysis shows that the team composition and communication at the bedside had following general characteristics: attendings dominated the conversation, producing 45.02 % of the interactions (as exemplified by utterances) in conversations during rounds. Residents were responsible for 21.60 % of the conversation, "other" clinicians for 13.27 %, and students for 10.07 %, and fellows for 10.04 % of the conversation. This pattern differed significantly from an even distribution of interaction among all clinicians on clinical rounds, $\chi^2(4) = 497.04$, $p < .001$. This shows some hierarchy in team communication at the bedside during clinical rounds.

Errors Generated and Corrected

We first examined interactions in terms of errors generated and corrected. Overall, 74.40 % of the utterances made were case information that contained neither an error nor a correction, 11.42 % of which were not directly to the case, 8.40 % were errors, and 5.53 % were errors that were corrected.

Residents and Attending physicians were responsible for the greatest raw number of errors generated (75 and 74 raw errors, respectively, or 31.65 % and 31.22 %

Table 5.4 Number of errors generated (percentage of total utterances), corrected errors, and unresolved errors by all clinician types

	Generated errors	Corrected errors	Unresolved errors
Clinician type	# (%)	#	#
Attendings	74 (5.83)	41	33
Residents	75 (12.32)	54	21
Fellows	25 (8.93)	19	6
Students	27 (9.51)	20	7
Other clinicians	36 (9.63)	19	17
Total	237 (8.40)	153	84

of errors in the sample). Other Clinicians made 37 errors (15.19 %), students made 28 errors (11.39 %), and fellows made 25 errors (10.55 %).

When analyzed in comparison to the number of utterances produced by expertise, residents made the most errors (12.32 % of their total utterances), followed by other clinicians (9.63 %), students (9.51 %), and fellows (8.83 %). Attendings made the fewest errors (5.83 % of their total utterances).

Examination of the raw frequencies revealed that attendings made over half of all corrections (82, or 52.56 %), despite only one attending being present on each observed round, residents made 27 (17.31 %) corrections, other clinicians, 19 (12.18 %), fellows, 18 (11.54 %), and the students made 10 (6.41 %) corrections. When considered against the utterances produced by level of expertise, attendings had the largest percentage of corrections (6.46 % of their total utterances), followed very closely by fellows (6.36 %), other clinicians (5.08 %), residents (4.43 %), and students (3.52 %). Even though residents made the second highest number of corrections, because they produced so many utterances during the rounds, corrections accounted for a very low percentage of their total utterances. Number of errors generated (percentage of total utterances), corrected, and unresolved by all clinician types is given on Table 5.4.

In summary, errors accounted for a small proportion of the total number of interactions. In terms of raw numbers of errors, residents made the most errors, and attendings followed closely. Relative to the respective amount spoken, the proportion of utterances that were errors was greatest for residents, and smallest for attendings. This result is somewhat different from the Kubose and Patel study, where the expert made most errors as well as corrected most of them. However, this study was conducted in a different hospital cardio-thoracic IUC (in a busy urban setting) unlike our current study, where data was collected in general medical ICU.

Conversational Analysis: Utterance Categorization

Examining utterances at the level of case management categories shows that the three categories that contained errors included information loss (76.54 %

Table 5.5 Frequency and percentage of clinician errors by expertise

Error category	Clinician expertise				
	Attending	Resident	Fellow	Student	Other
Information loss	61 (82.43 %)	57 (76.0 %)	16 (64.0 %)	20 (71.43 %)	27 (75.0 %)
Inaccurate interpretation	3 (4.05 %)	12 (16.0 %)	6 (29.0 %)	5 (17.86 %)	6 (16.67 %)
Faulty decision-making	10 (13.51 %)	6 (8.0 %)	3 (12.0 %)	3 (10.71 %)	3 (8.33 %)

utterances), with wrong interpretation (13.17 % utterances), and faulty decision-making (10.29 % utterances).

Of the categories of conversation that contained errors, information loss was the largest. The task at the bedside is to make decisions about the patient management using the information at hand. This requires filtering out irrelevant information to make immediate decisions, and information loss at this point could indicate an editing process of the extra information that was not immediately necessary.

When all the categories under case management containing errors were analyzed, information loss constituted the largest category of error for all clinician types. Inaccurate interpretation made up the smallest percentage of attendings' errors, but made up a large proportion of the errors made by all other clinicians. Table 5.5 shows the frequency and percentage of clinician errors as a function of expertise. The role of the expert attending clinician becomes important in correcting inaccurate interpretation.

The temporal order of the case management categories relates to how errors are corrected or unresolved temporally and semantically. We provide two illustrated examples from segments of transcripts rather than a whole transcript of team conversation, in Fig. 5.2.

Decision Flow and the Correction of Errors

Figure 5.2 represents a sequence of conversation over time. This section of transcript from the first round, Bed 2, illustrates how errors are generated and are corrected in the course of team interaction. Table 5.3 contains the corresponding transcript to demonstrate the coding process. The objects with the light green fill were utterances said by the attending, those with the purple fill were said by the fellow, and those with the blue fill were said by resident. The utterances contained in the red hexagonal shapes are errors, those in ovals are corrections, and rectangular shapes represent other information important to the case that is neither an error nor a correction. The black arrows show temporal sequence of conversation while the red arrows show the backtracking from corrections to the errors that they corrected.

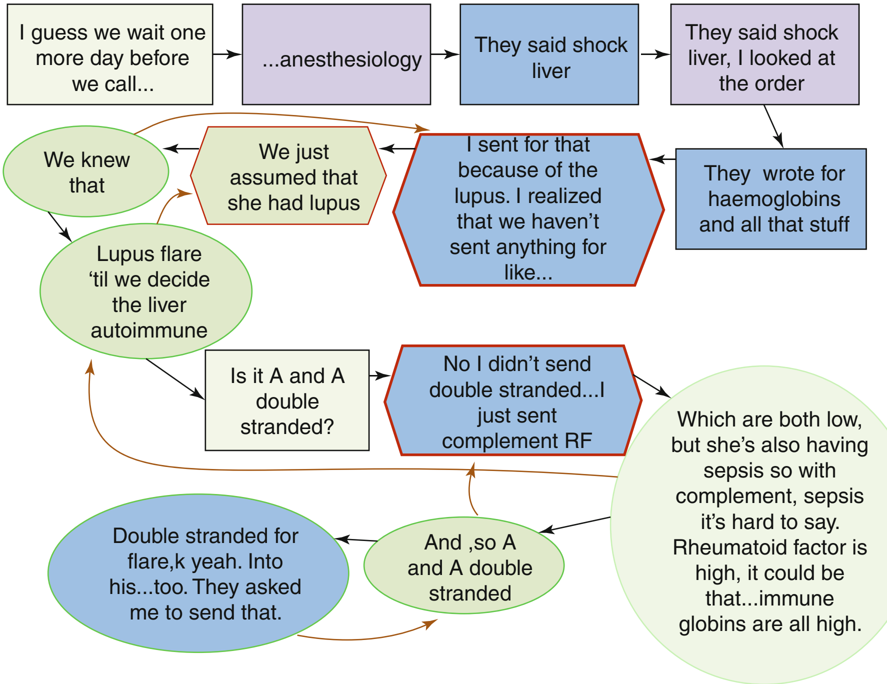

Fig. 5.2 An illustrative example of a decision flow diagram representing a segment of Team 1's interaction at the bedside of Bed 2 (See Table 5.3 for transcript)

An example of temporal events in a narrative text is given below:

Attending: So, is the Vanc ok? He is a little…yeah, you think we are going to over do it."
Interpretation asks if Vanc is at the right level
Resident: "When was it, yesterday?"
Interpretation asks when was Vanc given
Attending: "Ok. So if his urine output changes as his creatinine changes, we will re-check it again. Ok."
Interpretation: Will recheck Vanc if urine output changes

Although there is a temporal sequence to these utterances, there are also cognitive loopbacks from when the correction amends the error. One can see not only the flow of the conversation over time, but also the points in time when errors and corrections occurred and where the utterances refer to information that occurred earlier in the dialogue, illustrated by a backward directed flow. A similar pattern can be seen for Team 2, as shown in Fig. 5.3.

Figure 5.3 represents a sequence of utterances temporally as well as how errors are corrected from a section of transcript from the second round, Bed 4. The

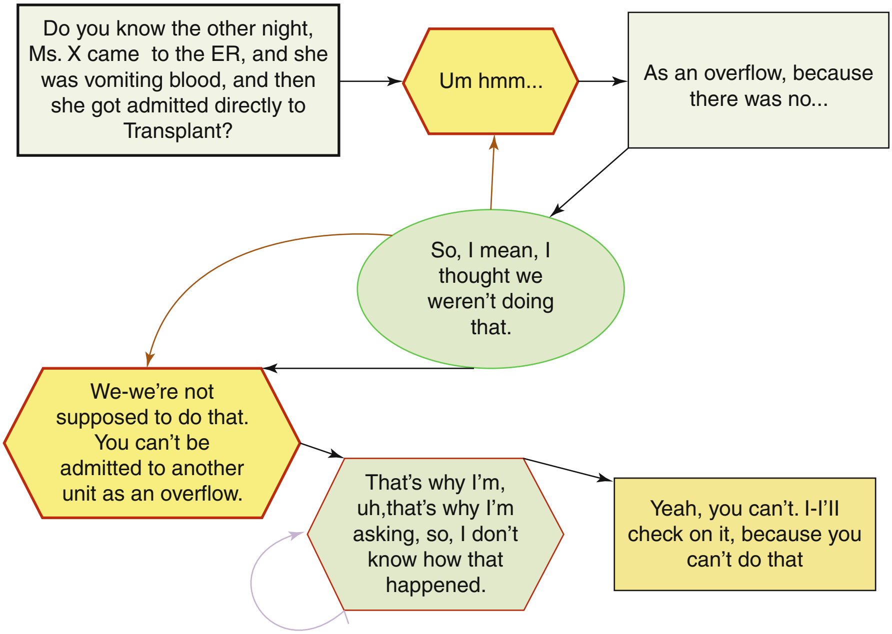

Fig. 5.3 An illustrative example of a decision flow diagram structure of a segment of Team 2's interaction at the bedside of Bed 4

transcript related to this figure is given on Table 5.6. The objects with the light green fill represent utterances made by the attending, while the nurse manager made those with the yellow fill. The utterances contained in the red hexagonal shapes are errors; those in ovals are corrections; rectangular shapes represent other information important to the case that is neither an error nor correction. The black arrows show temporal sequence while the red arrows show the backtracking from corrections to the errors that they corrected. The double-headed purple arrow represents an unresolved error.

As in Figs. 5.2 and 5.3 also shows the sequence of utterances as well cognitive loopback for a correction amending an error, or errors, but also shows an unresolved error and the possibility that it may propagate to patient care.

The example in Table 5.7 illustrates teamwork during clinical rounds. While the attending creates plans for the patient's care based on the underlying causes for their current condition, the resident and the fellow provide supporting information to assist in the attending's decision-making.

Relationship Between Error Correction and Error Propagation

Figure 5.2 represents a scenario where the error, or rather errors, was corrected to the point of what seems to be a resolution. This scenario involved errors surrounding the false assumed diagnosis of lupus, as well as sending for a test because of this

Table 5.6 Corresponding Clinical Round Transcript segment of Fig. 5.3

Type of clinician	Transcript text	Case management	Error type	Interpretation
Attending	Do you know the other night, Ms., Ms. ____ came to the ER, and she was vomiting blood, and then she got admitted directly to Transplant	Information aggregation	N/A	Asking nurse manager rhetorically if she knew of an issue with a patient
Nurse manager	Um hmm…	Faulty decision	Corrected error	Admitted patient directly as a transplant, can't do that
Attending	As an overflow, because, there was no…	Information aggregation	N/A	Letting nurse manager know the situation
Attending	So, I mean, I thought that, we weren't doing that, but.	Information aggregation	Corrected error	Corrects the notion that this procedure is allowed
Nurse manager	We-we're not supposed to do that. You can't be admitted to another unit as an overflow.	Faulty decision	Corrected error	Can't be admitted to another unit as overflow
Attending	That's why I'm, uh, that's why I'm asking, so, I don't know how that happened.	Information loss	Unresolved error	Doesn't know how that happened
Nurse manager	Yeah, you can't. I-I'll check on it, cause you can't do that.	Management decision	N/A	Agrees that this isn't correct and will check on the reason for this

assumed diagnosis, and the mistake of not sending out a particular test at all. The temporal order, or the path of the black arrows, shows the flow of information being given at each sequential slice of time, such as thinking the lupus test was not sent, then the assumption of lupus, and then the revelation of the team already knowing the test was sent. The cognitive loopbacks show how the corrections go back to rectify the errors made. For example, the team knowing the test was sent corrected the thinking that the lupus test was not sent. Sometimes two corrections will correct one error because of the semantics of the statements and the knowledge pieces that need to be put together. This can be clearly seen in the path of the red arrows.

In contrast, Fig. 5.3 represents a scenario where two errors are amended by one correction and one error is unresolved. The attending physician's utterance, "So I mean, I thought that, we weren't doing that," corrects both of the nurse manager's

Table 5.7 Clinical Round Transcript segment from Bed 5, Day 2

Type of clinician	Transcript text	Case management	Error type	Interpretation
Attending	Ok, we seem to have cultures yesterday. We still want him to get a perm cap, hopefully Monday if things start to defervesce on the weekend.	Management decision	N/A	Creates a plan for how to proceed given the patient's status
Attending	Because I am not sure he is really having renal recovery.	Information loss	Unresolved error	Does not know reason for current status
Attending	How much urine output do we have?	Additional information	N/A	Requests information
Resident	335	Information aggregation	N/A	Provides information
Fellow	345	Information aggregation	N/A	Provides information
Attending	355? 345? So, I mean that's something, but I am not sure.	Information loss	Unresolved error	Unclear results supporting the renal recovery hypothesis
Attending	Sure, I guess we'll just keep the foley then just to keep monitoring.	Management decision	N/A	Plans to continue monitoring condition
Attending	Ok, what is EUA yesterday?	Additional information	N/A	Requests information
Resident	I didn't write it down	Information loss	Unresolved error	Cannot provide information
Attending	His UA? We sent to UA for his fever.	Additional information	N/A	Attempts to clarify request
Fellow	…urine cultures are negative, blood cultures are negative, sputum cultures are negative	Information aggregation	N/A	Provides information

utterances, "Um hmm…" (In response to knowing that an error was made by sending a patient to an unit inappropriate for them) and "We-we're not supposed to do that. You can't be admitted to another unit as an overflow," because the nurse manager's utterances are of the same nature, since the nurse manager was either unaware or did not take appropriate actions to admit the patient to the proper unit. However, the error in which the attending did not know why the patient was admitted directly to the transplant unit was unresolved, since there was never a way to find out what really happened.

In summary, both Figs. 5.2 and 5.3 represent scenarios where errors are generated but then are corrected. However, in Fig. 5.3, the attending and the nurse manager attempt to resolve the misunderstanding, where the error remains unresolved.

Summary of Results and Discussion

In this section, we summarize our key findings from this pilot study.

The attending clinician spoke the most at the rounds, *generated many errors*, *but also made the most corrections*. This result is similar to the Kubose/Patel study of the ICU environment at another institution [22]. An expert's ability to correct or to recover from errors they generate in real world ICU appears to be more generic, as it reflects the findings from studies outside of medical domain.

Two-thirds of the errors generated were corrected during the three clinical rounds, *leaving one-third unresolved*. There were a few self-corrections of errors during patient round discussions, while most errors were corrected by more experienced members of the clinical team, especially the attending. This result is unlike the results from Kubose/Patel study, where most errors were self-corrected by the expert, although senior clinical team members did assist in error correction. The nature of Cardiothoracic ICU appears to demand a different nature of task and urgency than the medical ICU errors. The unresolved errors were picked up later in the discussion in the surgical unit, but we did not analyze the MICU rounds data any further to look at unsolved errors over time.

For all levels of expertise, *information loss was the biggest category of errors*. Large amounts of information has to be managed at the bedside such that relevant information is on focus for making quick decisions to manage the patient. Information loss is inevitable at this stage. However, any loss of information that is clinically relevant at the point of care at that moment can lead to adverse consequences for the patient. In the surgical ICU study, the focus was on the minimum amount of information that was necessary to deal with the patient at hand. This could relate to the nature of the patients in medical and surgical ICU.

There are many factors (e.g. time pressure, multitasking) that play a role in decision making in the naturalistic, complex working environment of the ICU, creating greater opportunities for the clinical team to generate errors, as compared to the semi-naturalistic conditions and lab-based studies. Patient management plans for one patient is completed before moving on to another patient, making sure that there are not too many problems left unresolved, leaving little time or lengthy discussion of any errors. They are quickly corrected, where possible. In the surgical ICU, the time pressure and multitasking are big factors, given that the unit has many technologies and the team uses these constantly during the clinical rounds. This is somewhat unlike the MICU environment.

In our previous research, individual clinicians allowed more errors in a sample case to propagate to the level of care than the teams in a semi-naturalistic study. In the current study, set in a naturalistic setting, errors were corrected at a ratio of 2 to

1. These errors were not exclusively patient management errors, of the sort embedded in our laboratory-based and semi-naturalistic examples. Rather, errors in information transfer and interpretation were more frequently encountered. The teams performed better in detecting and correcting errors, given the goal-directed nature of tasks in an ICU environment. It appears that the complex environment of critical care also helps in creating error checks, where people are on high alert.

Conclusions and Final Comments

The results from this pilot study in the MICU, together with the results from the earlier study by Kubose/Patel, add to our understanding of the nature of error generation and correction in the ICU in an in-vivo situation. The results of the pilot studies necessitate more careful systematic investigation of team interactions for decision-making in critical care and the pressures that push clinicians to make mistakes as well as to correct them. We will provide our final comments on the next steps in our investigations as well as some thought on the relationship between performance and learning in critical care.

Our earlier studies show that physicians' ability to detect errors in clinical problems in the intensive medical care domain is limited when tested individually in laboratory-based conditions (Chaps. 3 and 6). We extended this study to explore the mechanism of error detection and correction when working in teams, using (a) semi-naturalistic and (b) naturalistic empirical paradigms. The data were collected in a medical intensive care unit and were analyzed for the process of patient management and the frequency and nature of errors generated and corrected. The results show that the teams perform better than individuals, due to the advantages conferred by the distribution of cognitive tasks across multiple team members. Attendings and residents were found to generate more errors as well as recover from most of them in a real world setting. This was not the case in studies under other conditions.

However, in interpreting these results it is important to note the distinctions between this naturalistic work and our previous experiments that would limit the interpretation of our results. All of the errors embedded in the case scenarios used in our previous experiments were patient management errors (the subjects were asked to do evaluate the patient management), but most of the errors observed in practice were related to information loss related to direct patient care (because data had to be collected and aggregated). As discussed previously, attending physicians do not bear the burden of collecting and aggregating information. Rather, their clinician colleagues conduct this work.

Error detection and correction in a situation closer to complex real world practice appear to induce certain urgency for quick action resulting in rapid detection and correction. Here, complexity appears to put in some error checks. Furthermore, teams working at the bedside in real world optimize performance (finalizing decisions in very short period of time) with little room for explicating any mistakes and thus little learning from errors. There is a close relationship between competency in delivery of patient care and the need to minimize errors. This is juxtaposed with the competing demand for learning from errors, an essential part of the apprentice training process.

Errors in the healthcare environment can be fatal to a patient, and so the ultimate goal is to reduce or eliminate them. However, errors are also a necessary part of the learning process. During clinical rounds (also known as *teaching rounds* or *patient rounds*), the team is focused on patient management to provide competent patient care. Another purpose of these rounds is to mentor trainees and elaborate on the mistakes individuals or the teams make, in order to ensure that trainees are given the opportunity to learn. In the real world critical care environment, clinicians minimize learning and optimize performance when the goal is to focus on patient care. However, this is not true for situations in which the real world is simulated and there is no danger of harming the patient. This later condition provides the opportunity to make mistakes and learn from them without compromising patient safety. A combination of both mechanisms with a feedback loop is thus required, which promotes both competent patient care and learning opportunities.

Discussion Questions

1. The airline industry has been successful in managing human error to a large extent, but this is not true in the healthcare system. Discuss some of the challenges related to the management of human error faced by the healthcare system (namely, critical care) that are distinct from those encountered in the aviation context.
2. Studies on error detection and correction by health professionals show different results in naturalistic (in-vivo) and laboratory-based (in-vitro) environments. Discuss some of the factors that may contribute to these differences.
3. One needs to generate errors to learn from them and yet generation of errors, if not corrected, compromises patient safety. How might one reconcile these two positions?

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