



Automatic Workflow Capture and Analysis for Improving Trauma Resuscitation Outcomes

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Introduction

Background: several studies have shown that errors in diagnosis and management during trauma and medical resuscitation can contribute to adverse outcomes, including death.

- Critically injured patients: 4X greater risk of errors
- 50% of preventable deaths related to errors in the resuscitation phase
- Advanced Trauma Life Support (ATLS) protocol compliance is associated with fewer errors and less severe errors

Working hypothesis: accumulated deviations from expected workflow during trauma resuscitation decrease the team's ability to compensate for major errors that lead to adverse outcomes.

Goal: develop a computerized decision support system that will monitor workflow and alert to errors, allowing remedial actions to prevent adverse outcomes.



Data Description and Preprocessing

Data Description: There are 48 (update currently we have 92) trauma resuscitation cases manually coded at the Children's National Medical Center, which includes 7983 events total. Medical experts on our research team have developed an expert workflow model of 58 required tasks (mandatory in most resuscitations) and 70+ acceptable additional tasks (optional based on patient attribute). This workflow model includes two main medical phases, primary survey and secondary survey.

Data Preprocessing: The complete expert workflow model of trauma resuscitation is complex, which includes sub-models for 4 different medical roles and 130+ different tasks. In this model, different medical roles may perform tasks concurrently and collaboratively. And some tasks are rarely performed according to patients' conditions. In our preliminary analysis, we analyzed 39 (out of 48) resuscitations (involving 1871 events) and focused on 42 required tasks of *physician surveyor*, a medical role who perform most of the tasks in the resuscitation.

Preliminary Results

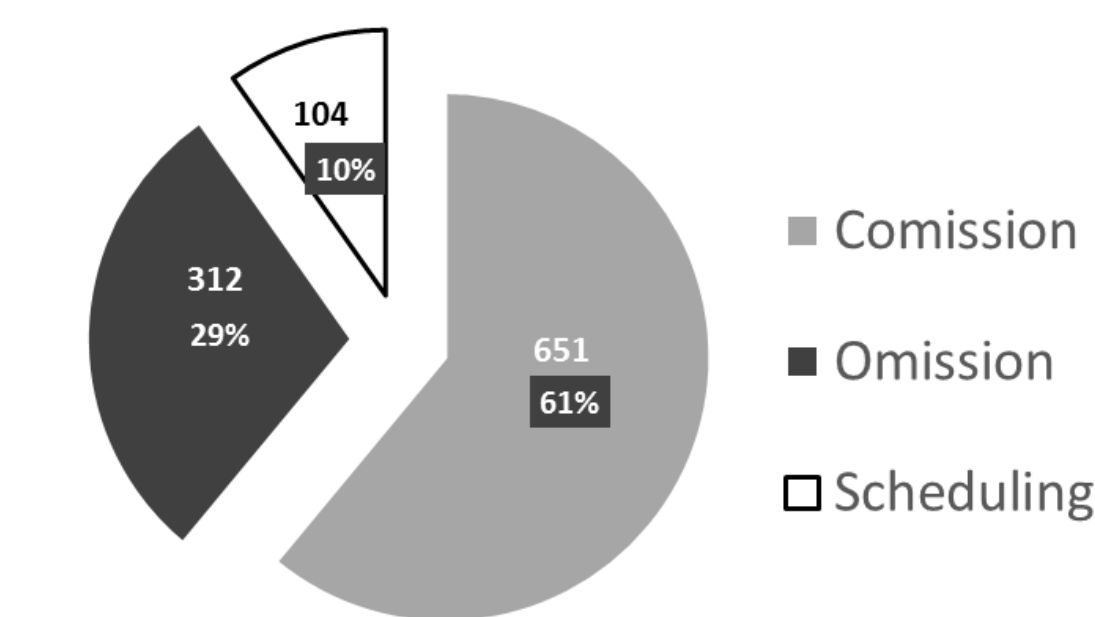


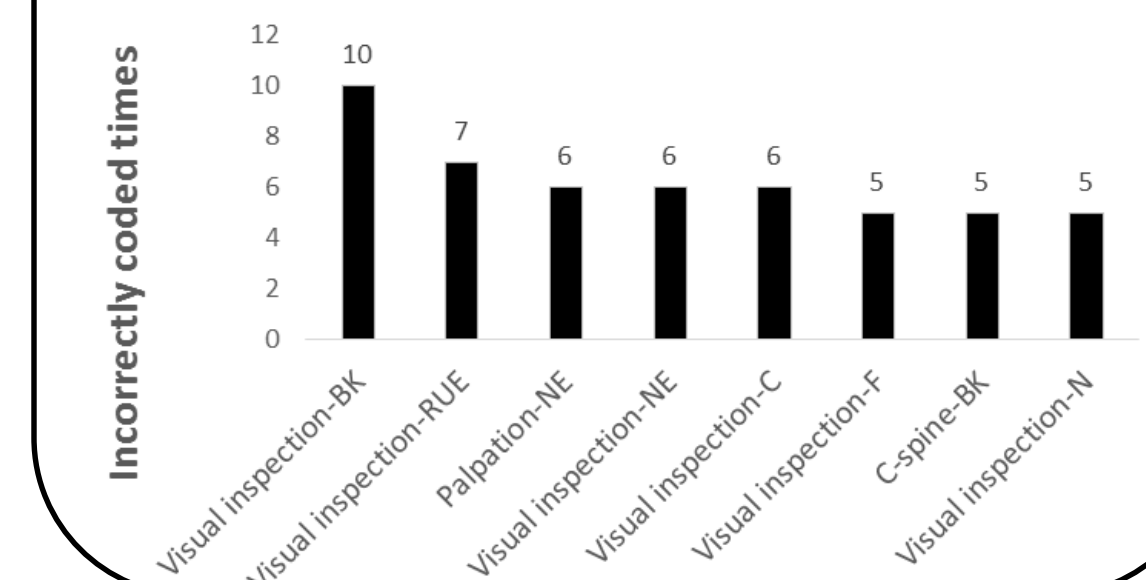
Figure. Process deviations classified based on behavior

Activity	Synchronized	Commission	Omission	Scheduling	TaskFitness
Log Roll-BK	2	0	38	0	0.05
L Visual Inspection-EY	8	5	32	0	0.18
R Visual Inspection-EY	8	2	30	2	0.19
L Otoscopy-EAR	16	2	19	5	0.38
L Visual Inspection-EAR	17	4	19	4	0.39
Visual Inspection-G	18	6	9	13	0.41
C-spine-BK	22	14	7	11	0.41
Visual Inspection-LLE	38	52	2	0	0.41
Palpation-NE	17	15	6	2	0.43
Palpation-LLE	37	44	3	0	0.44
Visual Inspection-NE	19	11	7	6	0.44
Visual Inspection-C	34	35	2	4	0.45
Visual Inspection-RLE	39	43	1	0	0.47

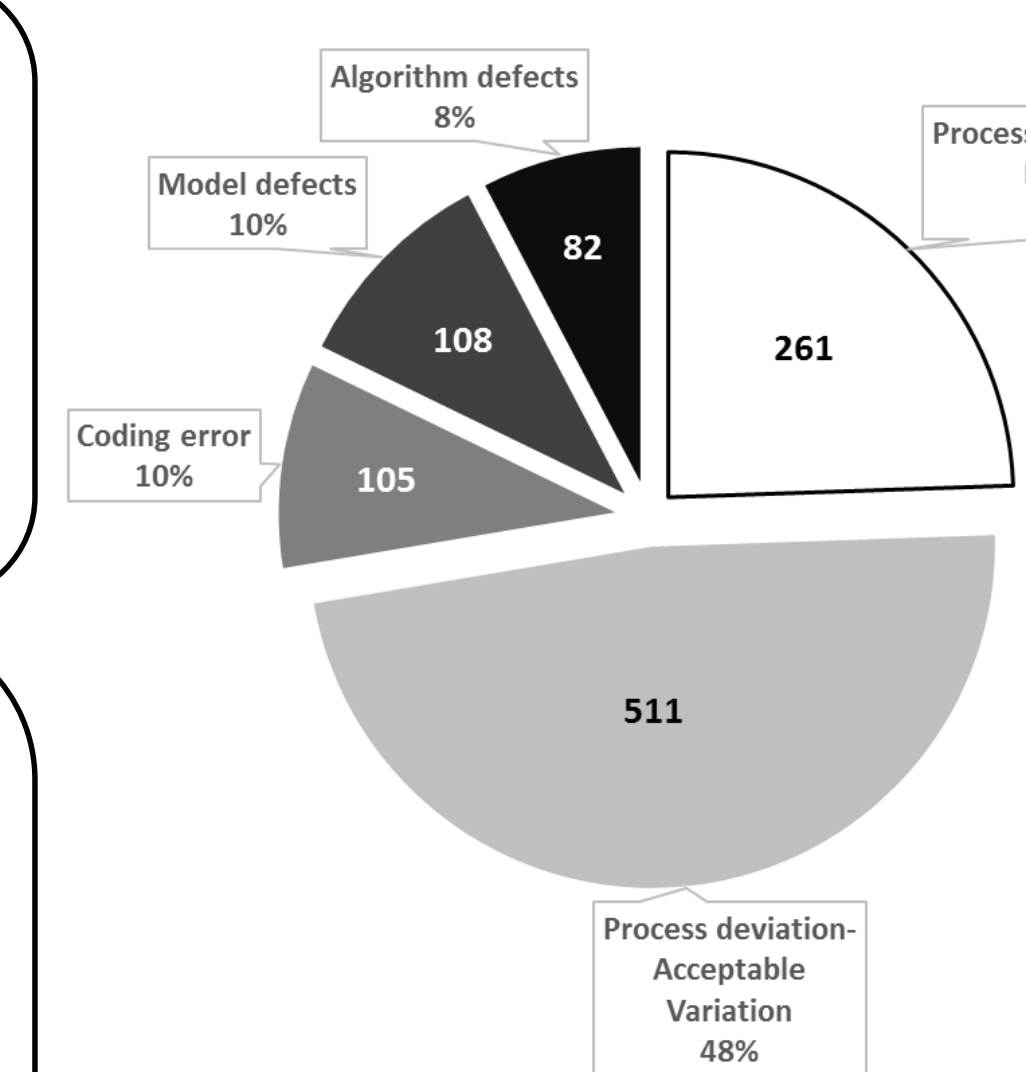
Table. Tasks that usually deviates from expert model

Model Errors: Some activities can be performed by other team members, e.g., L ear inspection and L otoscope can be performed by the EM attending/fellow or anesthesiologist. And log roll can be performed by pretty much anyone on the team.

Coding Error: (1) anatomical gray areas (2) coding for visual examinations can be subjective



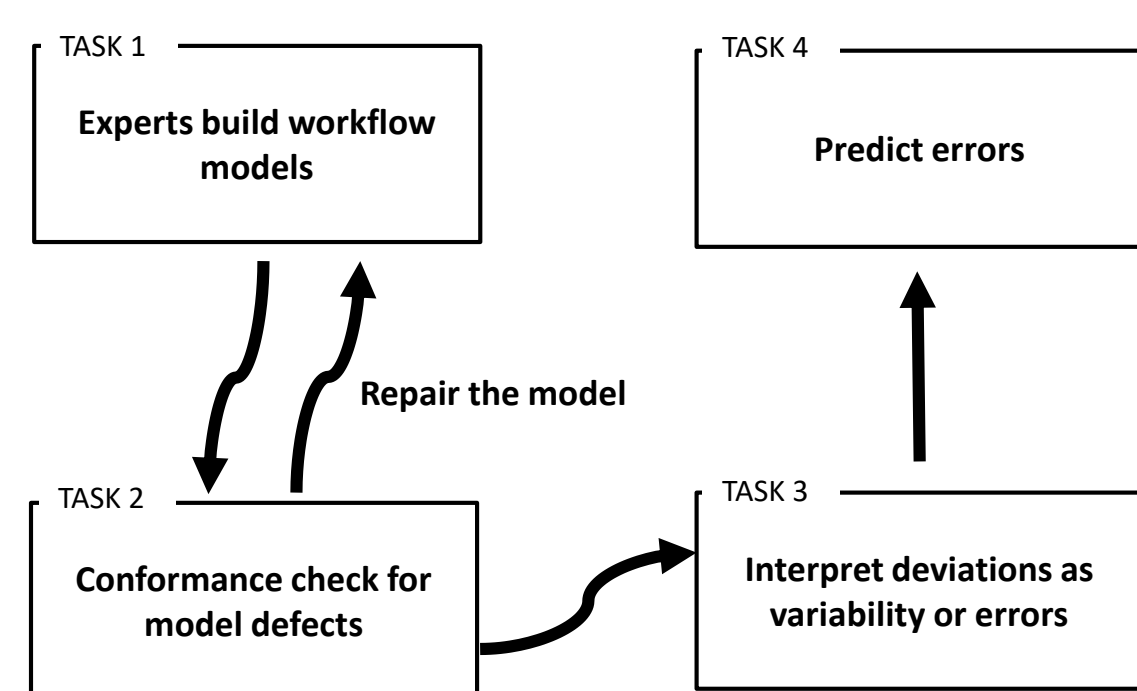
Algorithm Defects: conformance checking algorithm cannot achieve 1.0 accuracy, e.g., when duplicate activities exist, more information are usually needed to decide which one is deviation.



Acceptable variations: Most of the acceptable variations are consecutive repeated activities, e.g., physician checks the patients' eye repeatedly to make sure patients' injury. This type of deviations can be addressed by adding flexibility to expert model.

Errors: The errors with potential harm are the focus of our research which need much more detailed analysis.

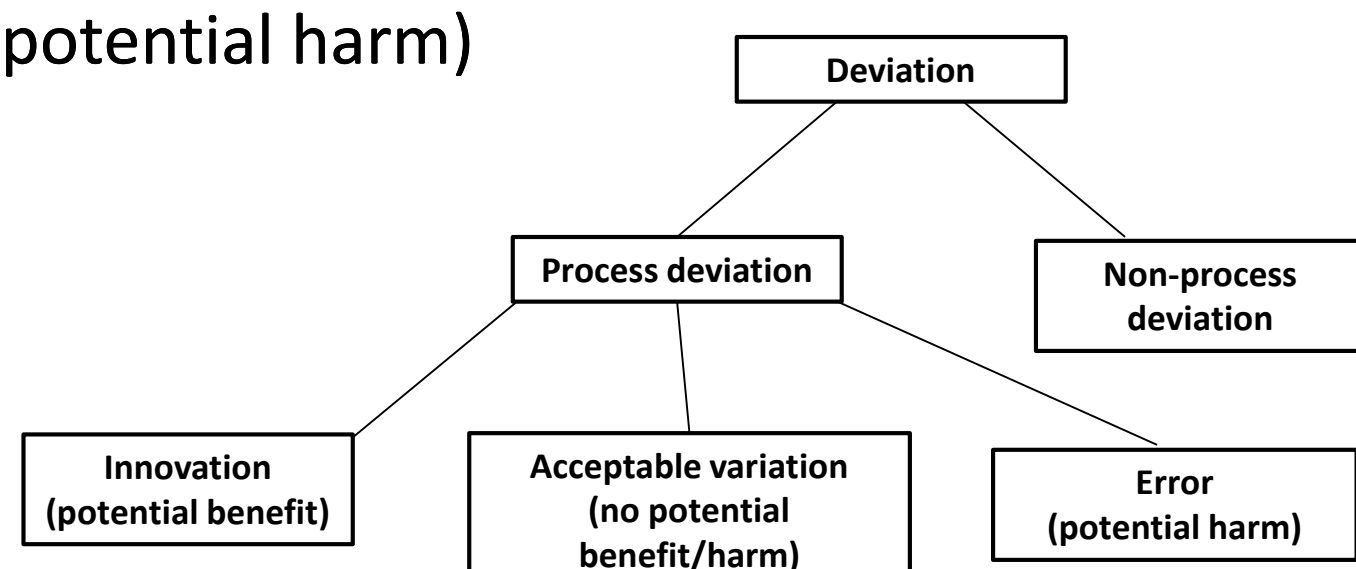
Objectives



Task 1: develop expert-based workflow models based on domain knowledge (e.g., ATLS protocol) as well as data-driven models discovered using process mining techniques.

Task 2: perform conformance analysis between workflow models created in Task 1 and resuscitation logs and group differences into four categories: (1) defects within the expert-derived models that require modifying or "repairing" these models to better represent practice, (2) process deviations, (3) conformance checking algorithm defects, or (4) other causes, e.g., coding error. Categories (1), (2), and (4) need to be addressed by iteratively repairing expert models, improving algorithms and modify coding errors. Only process deviations will be passed down to task 3.

Task 3: classify process deviations from Task 2 as tolerable variability or errors (potential harm)



Task 4: determine the association between major errors and process deviations that precede these errors. Predict errors.

Method

1) Build expert workflow model

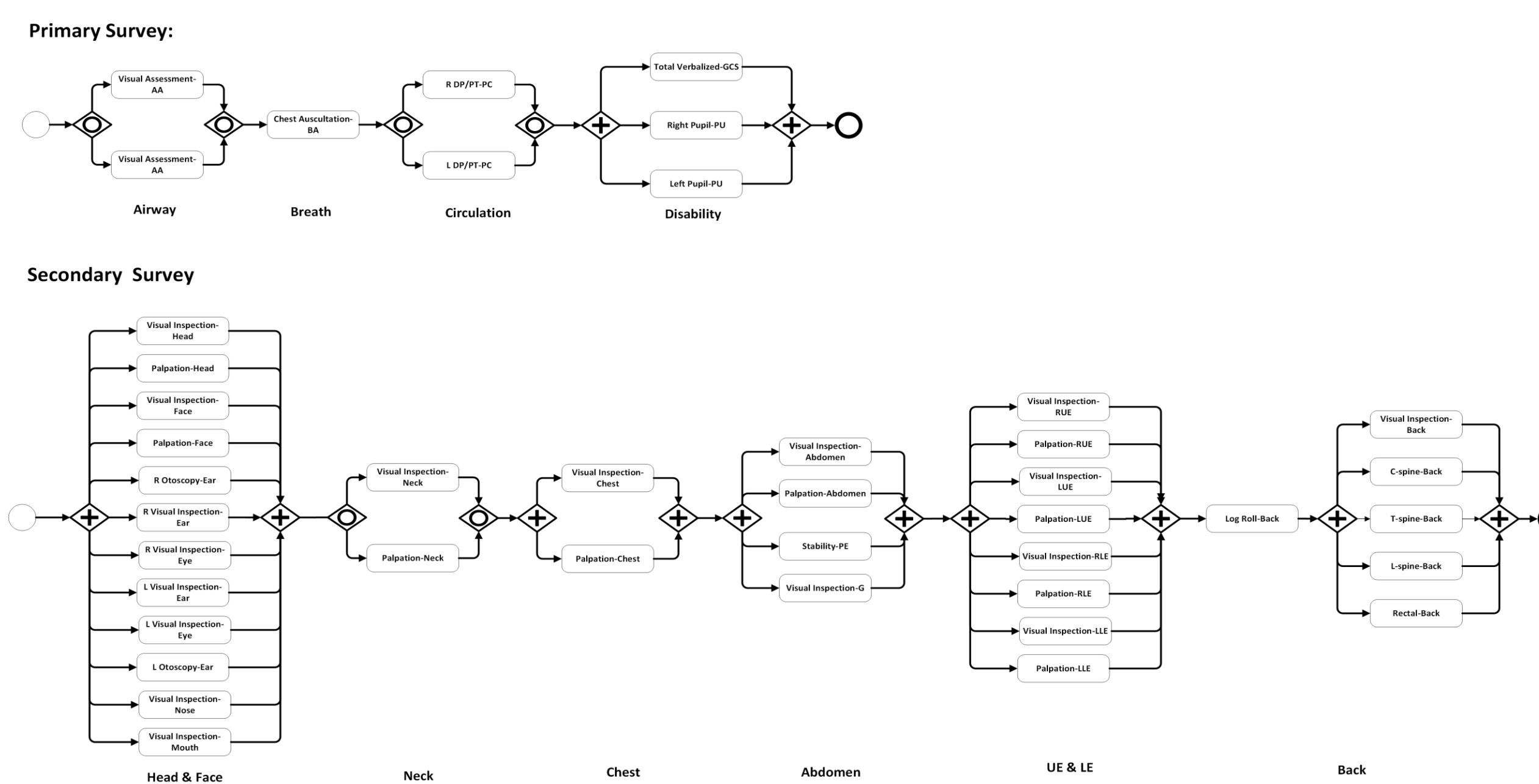


Figure. Expert model for diagnostic activities of physician surveyor

2) Check conformance between practical resuscitation data and expert model using ProM, an open-source process mining tool. Events that deviate from the expert model are labeled as process deviations (deviation of commission, omission, scheduling).

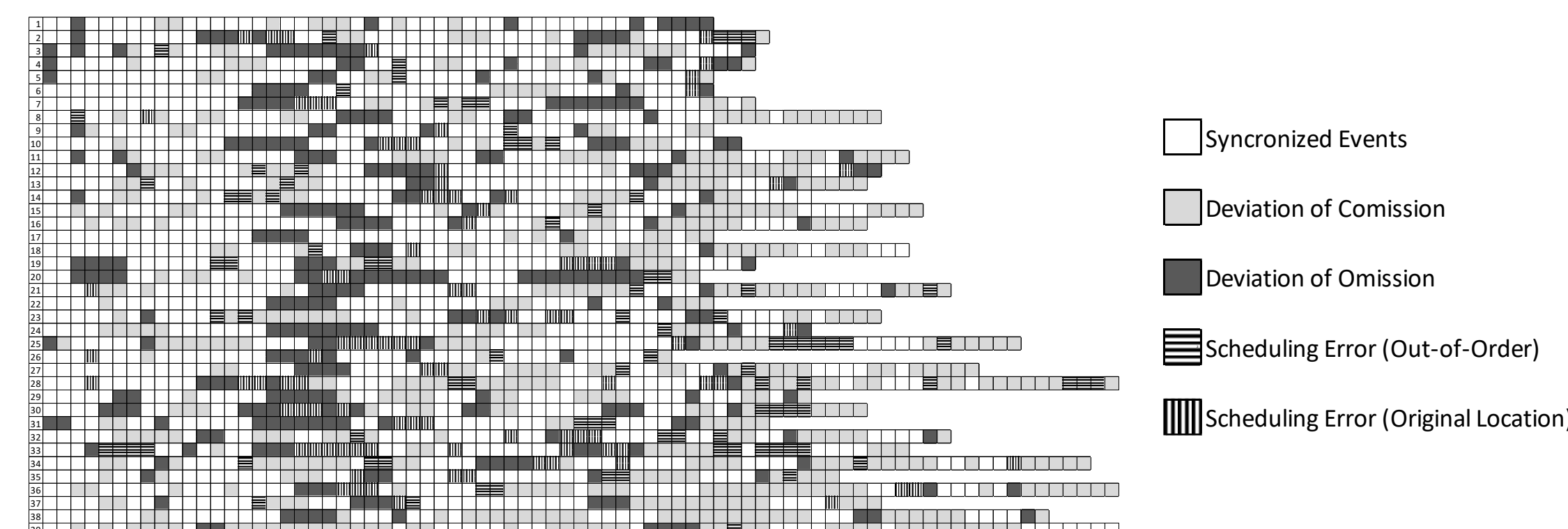


Figure. Visualization of deviations in workflow data

3) The process deviations are evaluated manually by medical expert. Based on the evaluation results, we reclassify the process deviations into four categories based on the causes.

- Model defects
- Process deviations
- Algorithm defects
- Coding errors

Limitations and Challenges

Small Data. Need to track workflow manually. No existing techniques can record the resuscitation data automatically

Real Time. Lack of method to monitor workflow in real-time to detect deviations associated with adverse outcomes

Variable Patients. Different patients may need different treatment procedure.

Permissible Deviations. Some deviations are acceptable. Need to distinguish permissible deviations from harmful deviations.

Concurrent Activities. The resuscitation is performed by a medical team where different medical roles working together on different tasks at the same time.

Acknowledgement

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