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A data-driven framework for improving clinical managements of severe paralytic ileus in ICU: From path discovery, model generation to validation

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Abstract. Paralytic ileus (PI) is a severe health condition associated with poor clinical outcomes and longer hospital stays. Due to the high variability in clinical pathways, identifying risk factors on high-frequency pathways may facilitate the efficient optimization of clinical processes. This paper illustrated a data-driven framework that combines local process optimization and conceptual model validation. Frequent clinic pathways and contributing factors were discovered by leveraging local process modelling (LPM) and Partial Least Squares-based Structural Equation Modeling (PLS-SEM). Principle component analysis (PCA) was used to identify latent factors. LPM was used to identify structural relationships in the high-frequent process pathways. PLS-SEM was adopted to evaluate the magnitude of relations. Through this framework, the study identified one frequent clinic pathway and six contributing factors for severe PI patients.

Keywords: Process Mining, Factor Analysis, Partial Least Square.

1 Introduction

Paralytic ileus (PI) is a severe clinical condition characterized by intestinal blockage and the absence of abdominal smooth muscle activation [1, 4]. In 2019, 10.1 million people worldwide were diagnosed with PI, resulting in over 7 million global disease burden measured by disability-adjusted life years [2]. Hospitalization for PI is particularly prevalent among people aged 65-79 years and is associated with increased cost of care [3]. The etiology of severe PI is multifaceted and lacks a precise mechanism [4]. The obstruction may arise from either mechanical or non-mechanical factors. Severe PI can be attributed to a variety of factors, including abdominal surgery, fluid imbalances, infections, and the use of analgesics and antidepressants [1]. Limited understanding of optimization of severe PI clinical pathway, especially severe patients in ICU, resulted

in a poor clinical outcome of PI patients, including high mortality rate and prolonged hospitalization in untreated individuals [5].

Electronic health records (EHRs) present a unique opportunity for managing PI patients in clinics, as they can capture comprehensive information on clinic activities, diagnoses, clinical outcomes, and expenditures. By utilizing EHRs to identify frequently occurring clinical pathways in episode care and risk factors for severe PI hospitalization, healthcare providers can optimize resource allocation and improve the clinic outcomes of severe PI patients.

Process mining is a novel technique that employs data mining algorithms and process modelling to analyze event logs recorded by a health information system. Local process model mining, as opposed to exploring end-to-end models, focuses on capturing frequent local patterns. Structural equation modelling (SEM) is a scientific investigation technique that uses visualization and model validation to explain pre-assumed causal relationships among latent constructs [6].

The aim of this study is to build a data-driven framework for supporting dynamic clinical management of severe PI hospitalization and uncovering common contributing factors to frequent clinic processes.

2 Method

The framework was constructed in five phases: cohort extraction, event log building, local process discovery, conceptual model building, and strategy generation (see Fig.1).

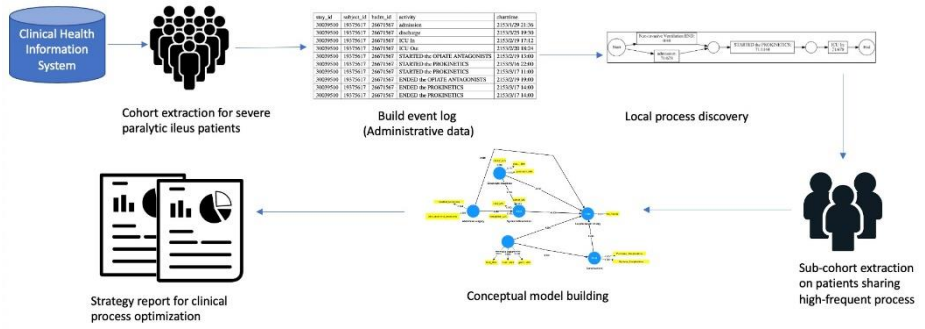

Fig. 1. Structure of a data-driven framework for optimizing clinic management in severe paralytic ileus patients.

2.1 Data Resource

MIMIC-IV version 2.0, released on June 12, 2022, is a large-scale publicly available healthcare database corresponding to over 60,000 patients admitted to the Beth Israel Deaconess Medical Center in Boston in the United States [7-8].

2.2 Cohort extraction

A cohort of patients with severe PI and their episode care was extracted following criteria: Patients aged 16 and older, diagnosed with PI coded as ICD-10 code K56.0. admitted to ICU at least once, and with a medication record for Prokinetics, Opioid Antagonists or Laxatives.

This cohort was used to identify high-frequent local processes for patients with severe PI. After that, a sub-cohort containing severe PI patients who underwent the frequent local process was extracted from the original cohort. Hospital length of stay (LoS), defined as the length of time elapsed between a patient's hospital admittance and discharge, was calculated as an indicator of the clinical burden for severe PI patients. A longer LoS is indicative of a more complex treatment scenario and a greater burden for patients and healthcare providers.

2.3 Event Log Extraction

An event log refers to a collection of events, each with a timestamp that records the executed time. An event represents a unique execution of an activity, which is a well-defined step in the process, such as "laboratory test" [9]. A trace will represent the order of events, and all events in a single trace will be carried out by the same context, which is typically characterized in terms of patient treatment flows.

To extract the event log of the cohort, a quality-aware framework [10] was followed, and the extraction was further justified by domain knowledge. The resulting event log contains all the necessary therapy activities and their execution timestamps, including different types of abdominal surgery and medications for severe PI patients.

2.4 Frequent Patient Pathways Discovery

In contrast to end-to-end models, the process discovery through a local approach focuses solely on identifying local process models (LPMs) with a lower number of activities, usually between three and five [11]. The LPMs are then matched with the process tree to systematically investigate the frequent pathways, up to a predetermined model size [11]. For local process discovery, the LPMs developed by Tax et al. [11] were utilized, and the quality of the resulting local processes was assessed based on five metrics: *Confidence* measures the degree to which the event conforms to the LPM derived from the event log; *Determinism* indicates the level of predictability of future behaviors; *Language fit* is defined as the ratio of behaviors allowed by the LP observed in the event log; *Coverage* measures the frequency of events that can be identified in the log; *Score* evaluates the overall performance of the LPM based on the aforementioned metrics.

2.5 Structural Equation Modelling

We assumed that patients who follow the same clinic pathways would share common characteristics and risk factors. However, establishing the connections between multiple factors can prove to be a challenging task.

In this study, principal component analysis (PCA) was adopted to generate hypothesis and identify potential contributing factors. Partial Least Squares-based Structural Equation Modeling (PLS-SEM) is employed to understand the relationship among the identified factors, due to its effectiveness in handling multiple structural paths without any distributional assumptions on the data and accommodating both small and large sample sizes [12-13].

3 Results

Total of 647 suitable severe PI patients' records were extracted from MIMIC-IV version 2.0 described in Table 1. On average, these patients were 63 years old, with an age range from 21 to 96 years. Of the 647 patients, 65% (423) were male, while 35% (224) were female. The higher proportion of males may be attributed to the fact that female PI patients have been reported to have a higher in-hospital mortality rate and lower incidence [14]. The average length of hospital stay for these patients was 20 days, with a range of 1 to 137 days.

Table 1. Demographic summary for 647 hospital-admitted severe PI patients (the original cohort).

Demographic summary	**All subject, n = 647**		
Sex	Males	Females	People
Count, N (%)	423 (65%)	224 (35%)	647 (100%)
Age in years, Mean (SD)	63 (14.97)	62 (17.07)	63 (15.71)
Length of Stay in days, Mean (SD)	19 (15.29)	22 (15.84)	20 (15.51)

A total of 7985 clinic event logs have been compiled, and the leading 10 frequently occurring events have been summarized in Fig. 2. Treatment with prokinetics was found to be the most common activity for severe PI patients, followed by laxative treatment. The frequency of these two clinic activities was higher than the time of admission and discharge, suggesting that many severe PI patients may have received more than one episode of care involving prokinetics and laxatives. In-hospital death was identified as the 9th most common event, accounting for 1.5% of the total events, for severe PI patients.

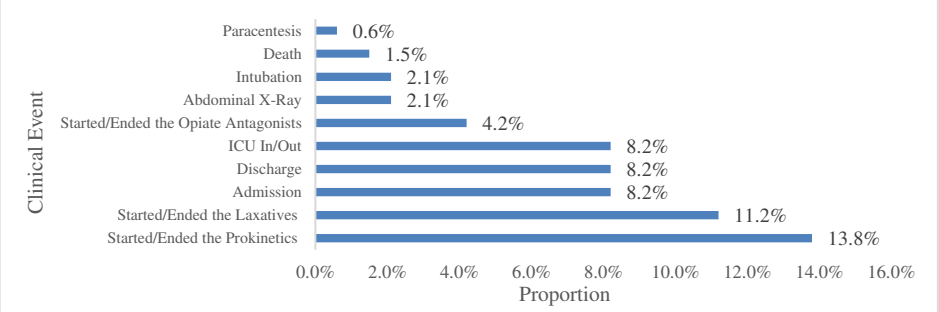

Fig. 2. Leading 10 frequent events for hospital-admitted severe PI patients.

Ten frequently occurring local processes have been identified through LPMs. Among these, we identified one local process that aligned with clinic practices and achieved the highest score (0.87) and best performance on the Confidence, Determinism, Language fit, and Coverage matrices (0.99, 1.0, 1.0, 0.24, respectively). Our findings suggest that, in severe PI hospitalizations, patients were typically transferred to the ICU after being admitted to the hospital, followed by discharge from the index hospital (as shown in Fig. 3).

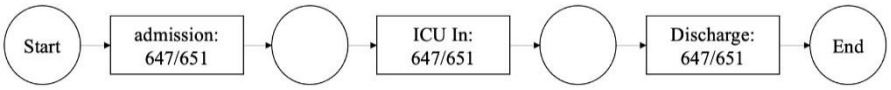

Fig. 3. Petri Net of showing high frequent severe PI patient pathway.

Following exclusion of in-hospital deaths, we identified 526 severe PI patients who followed the frequent pathway. Similar distribution of age and sex was detected in this sub-group when comparing to the full cohort. Of the 526 patients, 65% (344) were male, while 35% (182) were female. The average length of hospital stay for these patients was 20 days, with a range of 2 to 137 days.

hypothetical paths and selected risk factors were built up and tested by using PCA with several iterations. After conducting bootstrapping, PLS-SEM modeling identified six latent constructs and 24 factors that may potentially affect clinical outcomes for severe PI patients in the frequent clinic process (see Fig. 4). The strength of each structural path, determined by the R^2 value for the dependent variable, indicated that this conceptual model accounts for 31.9% of the observed variability in the LoS. Furthermore, the regression model explains 13.2% of the observed variability in complications and 7.1% of the observed variability in systemic inflammation. Model goodness of fit was measured by standardized soot mean square residual (SRMR), which reflects 7.2% of the discrepancies between observed and expected correlations in the conceptual model.

Table 2. Summary of PLS-SEM modelling statistics.

Path	Sample mean	STDEV	T statistics	P values

Abdominal surgery → System Inflammation	0.42	0.27	1.55	0.12
Complications → Hospital length of Stay	0.42	0.01	4.95	< 0.001
Electrolyte Imbalance → System Inflammation	0.25	0.04	5.60	< 0.001
Electrolyte Imbalance→Hospital length of Stay	-0.21	0.04	4.97	< 0.001
Metabolic Disturbance → Complications	0.17	0.02	8.71	< 0.001
Metabolic Disturbance →Hospital length of Stay	0.18	0.05	3.97	< 0.001
System Inflammation →Hospital length of Stay	-0.25	0.03	8.40	< 0.001

Table 2 describes the model, including path coefficients and P values. Six components, with eigenvalues larger than 1, have been identified through PCA. According to the conceptual model, complications and metabolic disturbances have a significant impact on LoS, while abdominal surgeries and electrolyte imbalances may be associated with systemic inflammation. No significant difference on the results of PCA and PLS-SEM modelling after sex stratification.

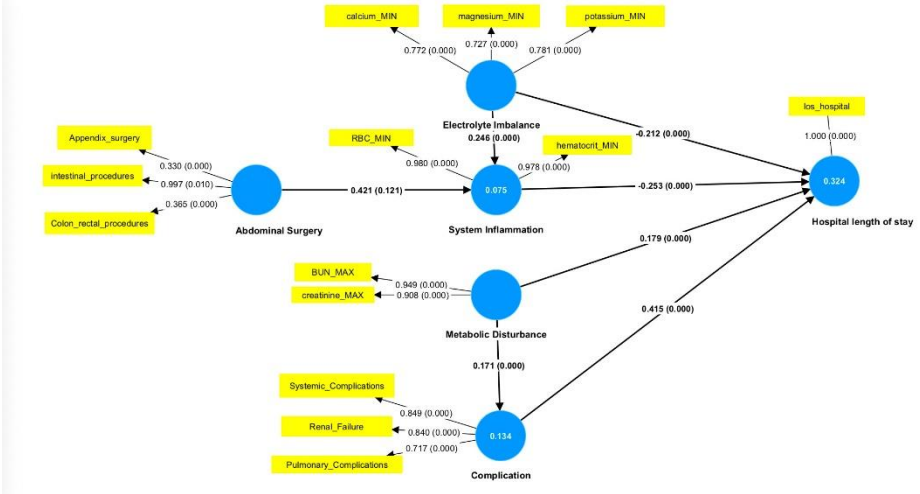

Fig. 4. Conceptual model for contributing factors in the frequent clinic pathway. Blue nodes represent constructed latent factors; Yellow cubes reflected including variables; Number on each path represented path coefficient (P values): P-value less than 0.01 indicated strong evidence.

4 Discussion and Conclusion

This study illustrated a data-driven framework, starting from pathway discovery and progressing to model building, followed by model testing. This framework is aimed at enhancing the clinical management of severe PI in the ICU, utilizing LPM and PLS-SEM techniques. Through PLS-SEM, both direct and indirect relationships have been uncovered along the pathways. It has been observed that metabolic disturbance has a direct impact on LoS and also exerts an indirect effect on LoS through the mediation 'Complications'. However, the relationship between electrolyte imbalance and

systemic inflammation with LoS should be interpreted with caution. Based on current evidence [15-16], there is no consistent relationship among the three constructs.

The low score of item-to-construct reliability may need further investigation. Investigation of combining domain knowledge for paths as well as valid features measuring the events that have direct or indirect associations to outcome will be future direction. As hypotheses generation tools with clinical and administrative domain experts for inputs to generate realistic hypotheses for statistical testing would significantly enhance the applicability of mined outcomes in clinical practice. Evidence derived from current research to support conceptual model building and evaluation would ensure the quality of proposed clinical strategies.

Nonetheless, the absence of information on procedure duration and medication administration time in this secondary data may impede our understanding of their roles in clinical processes for severe PI patients. Exploring datasets that encompass these clinical activities may uncover more accurate optimizing strategies. Moreover, the current framework mainly focuses on frequent clinic pathways, so patients who received uncommon treatments and their specific needs have not been fully discovered.

Local process models (LPMs) may create loop routes, resulting in excessive redundancy. The repeated clinical patterns from the LPMs may further augment the working burden of evaluation for healthcare providers and administrators. An alternative algorithm for local process modeling is necessary.

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