Process Mining for Demographic Insights: A Subpopulation Analysis in Healthcare Pathways

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Abstract: Demographic variations in healthcare pathways are key for delivering effective and equitable patient care. Examining pathway differences across age and gender groups can help uncover demographic-specific disparities in care delivery. In this paper, we demonstrate the use of the Process Mining Project Methodology in Healthcare (PM^2HC) for the subpopulation-based analysis of treatment pathways, using process mining techniques. We validate this methodology through a case study on frozen shoulder treatment using the MIMIC-IV data set. Key findings reveal distinct procedural sequences for male and female patients, as well as notable age-based variations in treatment choices and timelines. These insights underscore the influence of demographic factors on healthcare processes. Expert evaluations further highlight the practicality of the methodology and its potential to guide targeted interventions that address various patient needs, thus enhancing personalized care. This work contributes to clinical research and practice by identifying inefficiencies and informing tailored interventions. Future efforts will extend the methodology to other medical conditions and integrate multi-institutional data for broader applicability. By advancing process mining in healthcare, this research provides insight into improving patient care and addressing demographic diversity.

1 INTRODUCTION

Process mining techniques have demonstrated their capabilities to uncover inefficiencies and deviations by analyzing event logs (van der Aalst, 2011). In healthcare, these techniques can identify delays in diagnosis, disparities in treatment effectiveness, and variations in access to therapies (Huang et al., 2013; Guzzo et al., 2022). In the domain of process mining, obtaining an accurate representation of patient care pathways is key. However, this task is inherently complex and challenging (Mans et al., 2009; de Boer et al., 2024).

Subpopulation methodologies offer a structured framework for analyzing variations in healthcare care pathways, providing insight into how demographic factors, such as age and gender, influence treatment and outcomes (Campbell, 2013; Partington et al., 2015; Rademaker et al., 2024; Scholte et al., 2023). Improving healthcare delivery increasingly relies on approaches that address patient diversity. By isolating specific patient groups, subpopulation analysis allows healthcare professionals to identify distinct care paths, detect inefficiencies, and design personalized interventions that improve patient outcomes and streamline processes (West et al., 2008; Rotter et al., 2019; Chen et al., 2023). However, despite the prevalence and widespread consideration of distinguishing clinical pathways (Vanhaecht et al., 2006), barriers remain, particularly at implementation levell (Evans-Lacko et al., 2010; Neame et al., 2019).

Focusing on specific patient subgroups simplifies analytical workflows, yielding insights directly relevant to clinical decision-making. For example, frozen shoulder (FS) cases often exhibit demographically driven differences in care processes (Rababah et al., 2020), influenced by factors such as age, gender, and health status. Analyzing these variations supports the development of tailored interventions, enhancing both the responsiveness and effectiveness of healthcare delivery. Clinical pathways have been shown to reduce hospital length of stay and costs significantly for invasive procedures, though their effect on

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readmissions and complications appears limited, suggesting further refinement in protocol design (Rotter et al., 2008). Further investigations into the use of analytically-driven protocols would allow investigators to identify opportunities for enhancing the patient's care path (Neame et al., 2019).

In this study, we use the Process Mining Project Methodology in Healthcare (PM^2HC) to perform subpopulation analysis, with FS treatment serving as our case study. By revealing demographic trends and treatment pathways, our study demonstrates potential for informing targeted interventions. A preliminary evaluation with domain experts underscores its practical viability, bridging theoretical constructs and clinical application, strengthening the generalizability of process mining in healthcare.

Developing a validated methodology for subpopulation analysis is key for ensuring both rigor and relevance (Gonzalez and Sol, 2012; Wieringa and Moralı, 2012). The intrinsic complexity and heterogeneity of healthcare data (Becker et al., 2021; Ma et al., 2021; Dasaradharami Reddy and Gadekallu, 2023; Guo and Chen, 2023) demand a structured approach that yields consistent and reproducible insights, particularly for subgroup-specific variations. Such a methodology underpins personalized care by considering demographic-specific needs, mitigating health disparities, and improving overall patient outcomes.

The paper is organized as follows. Section 2 provides an overview of related work. Section 3 details the methodology. Section 4 presents the findings from the case study. Section 5 gives a discussion. Finally, Section 6 concludes this article.

2 RELATED WORK

2.1 Subpopulation Analysis in Healthcare

In the literature, we observed most subpopulation analyses focus on improving care pathways by tailoring interventions to specific demographic factors. For example, age- and gender-based subpopulations are frequently considered in efforts to customize healthcare delivery and optimize patient outcomes (Partington et al., 2015; Scholte et al., 2023; Rademaker et al., 2024).

The paper (Rademaker et al., 2024) introduced a sub-population comparison framework for analyzing treatment procedures across different subpopulations sepsis patient groups. Using process mining techniques, their approach identifies indicators for improving care pathways, with age emerging as a significant demographic factor; an aspect explored in greater detail throughout this article.

Sub-population analysis is particularly valuable for chronic diseases, where patient heterogeneity often results in varying treatment responses. For example, studies in diabetes management have demonstrated that personalized interventions based on subpopulation characteristics, such as age and blood pressure, can enhance glycemic control and reduce complications (Valero-Ramon et al., 2020). Similarly, research in oncology has shown that analyzing subpopulations based on disease progression enables more targeted and effective therapies (Amatya et al., 2021; Alrawabdeh et al., 2023).

One of the main objectives of subpopulation analysis is to shift away from a one-size-fits-all approach, facilitating individualized, data-driven clinical decision-making. This analytic method helps to uncover complex patterns that might be overlooked in broader analyses. However, several challenges remain, such as ensuring access to high-quality data, addressing biases in subpopulation definitions, and balancing ethical considerations related to patient stratification (Sohail et al., 2021).

2.2 Process Mining Applications in Clinical Pathways

Process mining play a key role in identifying gaps between intended care protocols and their real-world execution by mapping actual care processes, thereby providing actionable insights to optimize care delivery. This capability is particularly critical in complex healthcare environments, where the involvement of multiple stakeholders and unpredictable patient trajectories often result in process fragmentation and suboptimal outcomes (Aspland et al., 2021).

Key applications of process mining in clinical pathways include evaluating patient flow within healthcare facilities, assessing compliance with clinical guidelines, and optimizing resource allocation. For example, (van der Aalst, 2016) demonstrated the potential of process mining to reduce waiting times and enhance care coordination by detecting process deviations. Furthermore, integrating process mining with subpopulation analysis enables healthcare practitioners to uncover variations in care pathways that reflect underlying differences, facilitating more precise interventions and targeted resource allocation (Mans et al., 2009; de Boer et al., 2024).

3 APPLICATION OF PM^2HC

The methodology adopted in this research is PM^2HC (Pereira et al., 2020), which comprises six phases. This section introduces FS as case study and elucidates how each of the phases is applied.

3.1 Frozen Shoulder as a Case Example

This study examines different stages of FS and its subpopulation groups. FS progresses through three stages: the freezing stage, the frozen stage, and the thawing stage (Rababah et al., 2020). During the freezing stage, patients experience nocturnal pain and restricted shoulder movement. The subsequent stage is characterized by reduced joint pain but a progressive loss of range of motion. In the final thawing stage, patients see further pain reduction and a gradual return of mobility.

FS, or adhesive capsulitis, is marked by fibrosis and rigidity of the glenohumeral joint, leading to a decreased range of motion in the shoulder joint (D'Orsi et al., 2012). This condition is more prevalent in females than males and typically occurs between the ages of 40 and 60 (Neviaser and Hannafin, 2010).

Treatment options for FS include conservative methods, such as physical therapy, and non-conservative surgical interventions, like capsular release (Mena-del Horno et al., 2022). Non-conservative treatments require the admission of FS patients to the Intensive Care Unit (ICU).

3.2 Planning

In the planning phase, we identified subgroups for distinct care path investigation. A brief background study on subpopulation analysis via process mining in healthcare is discussed in Section 2.

Subgroups were defined based on age and gender, given their significant influence on FS development (Koorevaar et al., 2017). We used the MIMIC-IV database, encompassing data from approximately 300,000 patients admitted to a tertiary academic medical centre in Boston, USA, from 2008 to 2019 (Goldberger et al., 2000; Johnson et al., 2021).

3.3 Extraction

We extracted data from the MIMIC-IV database (Johnson et al., 2023), which classifies patient diagnoses at ICU discharge using International Classification of Diseases (ICD) Version 9 and 10 codes. The initial task was to identify ICD codes related to FS in the "D_ICD_DIAGNOSES" table using the keywords "frozen shoulder" and "adhesive capsulitis" in the "long_title". The corresponding ICD codes, versions, and diagnoses are detailed in Table 1.

Subsequently, we identified all patients diagnosed with conditions listed in Table 1 from the "DIAGNOSES_ICD" table, where the "subject_id" and "hadm_id" uniquely identify a patient and a patient's hospital admission, respectively. Note that a patient may receive multiple FS-related diagnoses during a single hospitalization.

To construct individual tables for each subgroup, we extracted the "anchor_age" and "gender" of the patients from the "PATIENTS" table. The "D_ICD_PROCEDURES" and "PROCEDURES_ICD" tables were used to identify the procedures performed on patients in each subgroup. We filtered the procedures to include only those pertinent to the diagnosis and treatment of FS, based on keywords associated with FS treatment options: shoulder, steroid, arthroscopy, magnetic resonance imaging, rotator cuff, physical therapy, range of motion testing, and injection of insulin. The inclusion of insulin injections is particularly relevant due to the common association between FS and diabetes in affected patients (Zreik et al., 2016).

The "D_ICD_DIAGNOSES", "DIAGNOSES_ICD", "D_ICD_PROCEDURES", and "PROCEDURES_ICD" tables were important as they contain diagnostic and procedural data for the patients, which is key for hospital billing and is endorsed by PM^2HC for its reliability (Pereira et al., 2020).

For the application of the process mining algorithm, we defined cases, events, start times, and end times. In both subgroup process comparison and bottleneck analysis, a case represents a patient's hospital admission, and events are the procedures billed to the patient. We used sequence numbers to indicate the order of procedures in the absence of stored start and end times.

Upon curating the necessary data and storing it in the appropriate BigQuery tables, these tables were exported as CSV files for subsequent analysis.

3.4 Data Processing

During this phase, CSV files encapsulating subgroup data were imported into ProM and converted into XES format. These XES files were visualized using the "LogVisualiser (LogDialog)" plugin. Table 2 provides a summary of the case, and event counts for each subgroup, as generated by LogDialog. To discern care pathway variations across patient cohorts,

Table 1: ICD codes, versions and diagnoses for frozen shoulder.

ICD Code	ICD Version	Diagnoses
7260	9	Adhesive capsulitis of shoulder
M750	10	Adhesive capsulitis of shoulder
M7500	10	Adhesive capsulitis of unspecified shoulder
M7501	10	Adhesive capsulitis of right shoulder
M7502	10	Adhesive capsulitis of left shoulder

additional filtering was applied using the “Filter Log on Event Attribute Values” plugin, enabling the exclusion of specific procedures from the care pathways to identify distinct differences.

3.5 Mining and Analysis

This phase entailed identifying care path discrepancies across subgroups in medication administration and procedural adherence during ICU stays. Process models were constructed using ProM[1] and Disco[2]. Process models for subgroup comparison were mined using the following ProM plugins: “Mine with Inductive Visual Miner”, “Mine Petri Net with Inductive Miner”, and “Convert Petri Net to BPMN Diagram”.

The Inductive Miner was chosen for its superior fitness, which quantifies the ability of the generated process models to replicate the cases in the event log (Bogarín et al., 2018). Initially, the “Mine with Inductive Visual Miner” plugin was used to create animations illustrating the sequence of processes. The settings used were an “activities” slider at 1 and a “paths” slider at 0.8, ensuring equivalence between the Petri net and Inductive Visual Miner models. Subsequently, the “Mine Petri Net with Inductive Miner” plugin was used to generate static process models for visual comparison, with a “noise threshold” set at 0.2 to accommodate minor deviations. Finally, the “Convert Petri Net to BPMN Diagram” plugin was used to convert Petri net models into BPMN diagrams for analysis via BPMNDiffViz.

The tool BPMNDiffViz [3] can be used to calculate graph similarity measures by comparing two Business Process Model and Notation (BPMN) diagrams and returning the minimal graph edit distance (GED). GED is defined as the minimum number of operations (e.g., insertions, deletions, or substitutions) required to transform one graph into another (Skobtsov and Kalenkova, 2019). In the context of process modeling, a lower GED indicates greater similarity between the two diagrams. However, the significance of these scores depends on the specific application and the thresholds defined by the user or domain. BPMN-DiffViz utilizes BPMN 2.0, one of the most frequently used standards for process modeling (Ivanov et al., 2015).

The results and their interpretations are provided in the subsequent section.

3.6 Evaluation

In this phase, insights obtained from the previous phase were leveraged to suggest improvements. Further details on this phase can be found in Section 5.

3.7 Improvement and Support

During this phase, stakeholders—such as medical professionals—determine the course of action for implementing the improvements. This step was conducted in collaboration with an expert physiotherapist in the Netherlands to discuss and evaluate the research findings (see discussion in Section 5).

4 CASE STUDY ON FROZEN SHOULDER TREATMENT

In this section, we describe the case study. First, we present subgroup demographics and data descriptions. Next, we describe the results regarding care path differences among various FS patient groups, focusing on gender and age-based variations.

4.1 Subgroup Demographics and Data Description

In discerning care path dissimilarities among patient groups, we formulated two guiding questions: (1) What distinguishes the care paths of male and female frozen shoulder patients? and (2) How do the care paths of frozen shoulder patients aged below 40, between 40 and 60 inclusive, and above 60 differ?

[1]https://promtools.org/
[2]https://fluxicon.com/disco/
[3]https://pais.hse.ru/en/research/projects/CompBPMN/

Table 2: Number of cases and events per subgroup.

Subgroup	Number of Cases	Number of Events
Female*	29	61
Male*	34	55
Age below 40**	8	18
Age between 40 and 60**	39	73
Age above 60**	16	25

* Includes patients from all age groups
** Includes patients from both genders

Care path comparisons among subgroups used three key terms: "parallel" for two procedures occurring in any order, "sequence" for one procedure following another, and "exclusive" for scenarios where only one of two procedures can occur. Visual comparisons were conducted using BPMNDiffViz with the TabuSearch algorithm, set to a maximum of 100 expansions and a tabu list, to efficiently generate precise results faster than other algorithms (Skobtsov and Kalenkova, 2019). Note that the BPMN diagrams use blue to denote matched elements between the subgroups, green for elements to be added, and red for elements to be deleted to transform one diagram into another.

The process models, created in ProM and Disco for subgroup process comparison and bottleneck analysis, are available in a GitHub repository[4].

4.2 Gender-Based Variations

Visual comparison of the care paths for male and female FS patients using BPMNDiffViz yielded a final score of 167. Statistics are provided in Table 3, and specific procedures performed exclusively on male or female patients are listed in Table 4.

The procedure "Release right shoulder joint, open approach" is performed on both male and female FS patients. However, in male patients, it follows "Repair right shoulder tendon, open approach". In contrast, in female patients, it follows "Replacement of right shoulder joint with reverse ball and socket synthetic substitute, open approach".

If performed on male patients, the procedure "Rotator cuff repair" is always the first and is exclusive of "Other local excision or destruction of lesion of joint, shoulder." In female patients, these procedures can occur sequentially.

If performed, the procedure "Other arthrotomy, shoulder" is always the first for male patients. It can be performed sequentially with "Other repair of shoulder", but for female patients, it follows "Other repair of shoulder".

"Skeletal x-ray of shoulder and upper arm" is exclusive to male patients, while "Magnetic resonance imaging of other and unspecified sites" is exclusive to female patients. Neither procedure is combined with other procedures.

In male patients, "Other repair of the shoulder" can be performed in parallel with "Division of joint capsule, ligament, or cartilage, shoulder" and in sequence with "Rotator cuff repair". These procedures are sequential and exclusive for female patients, as shown in Figures 1 and Figure 2.

In male FS patients, if performed, "Synovectomy, shoulder" is the final procedure, following "Rotator cuff repair" as the first procedure. In female patients, it is exclusive with "Rotator cuff repair". These sequences are illustrated in Figure 1 and Figure 2.

4.3 Age-Based Variations

We compared the care paths for patients in different age groups to identify variations. First, we compared patients under 40 with those aged between 40 and 60, using BPMNDiffViz with the TabuSearch algorithm, which yielded a final score of 135. Statistics are provided in Table 5 details the statistics, and procedures exclusive to either age group are listed in Table 6.

Patients under 40 undergo "Release shoulder joint" using a "Percutaneous endoscopic approach", whereas those aged 40–60 use an "External approach".

Figure 3 and Figure 4 illustrate that "Other arthrotomy, shoulder" is sequential with "Other repair of shoulder" for patients under 40, whereas for those aged 40–60, these procedures are exclusive. Similarly, "Synovectomy, shoulder" is sequential for patients aged 40–60 but exclusive for those under 40.

Next, we compared the care paths of patients aged between 40 and 60 with those aged above 60, resulting in a final score of 142. Statistics are detailed in Table 7, and differences in procedures are listed in Table 8.

[4] https://github.com/PriyaNaguine/Complete-Process-Models-Frozen-Shoulder

Table 3: Statistics for the comparison of the care paths between male and female patients.

	Percentage of Elements	Number of Elements
Matched elements	37%	35
Deleted elements *	33%	31
Added elements *	30%	28

* Refer to table 4 for the differences in elements

Table 4: Procedures performed on either male or female FS patients.

Procedure	Female	Male
Drainage of right shoulder joint, Percutaneous approach, Diagnostic		✓
Excision of left shoulder bursa and ligament, Percutaneous endoscopic approach	✓	
Excision of right shoulder joint, Percutaneous endoscopic approach		✓
Other total shoulder replacement	✓	
Release right shoulder joint, External approach		✓
Repair of recurrent dislocation of shoulder	✓	
Repair right shoulder joint, Percutaneous endoscopic approach		✓
Repair right shoulder tendon, Open approach		✓

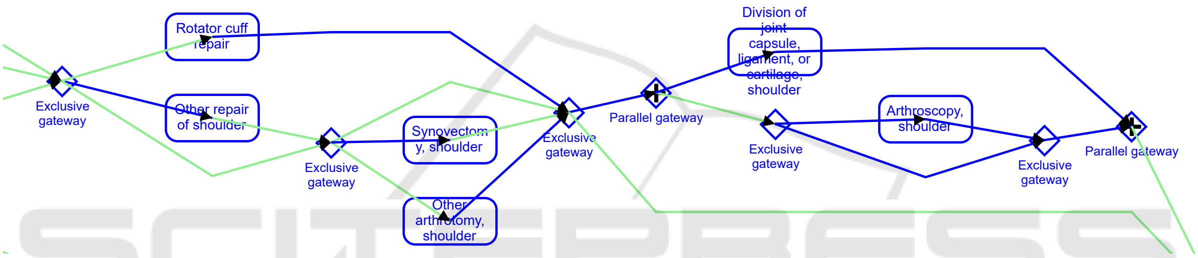

Figure 1: Snapshot of the BPMN diagram for female FS patients.

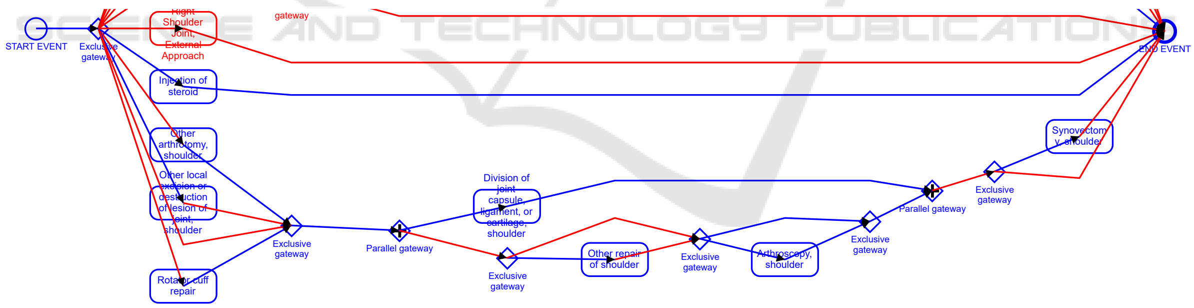

Figure 2: Snapshot of the BPMN diagram for male FS patients.

Table 5: Statistics for the comparison of the care paths between patients aged below 40 and patients aged between 40 and 60.

	Percentage of Elements	Number of Elements
Matched elements	49%	35
Deleted elements *	10%	7
Added elements *	41%	29

* Refer to table 6 for the differences in elements

Patients aged 60 and above undergo "Release right shoulder joint" using an open approach, whereas those aged 40–60 use an "External approach".

For imaging procedures, patients aged 60 and above receive "Skeletal x-ray of shoulder and upper arm", while those aged 40–60 undergo "Magnetic resonance imaging of other and unspecified sites". These procedures are exclusive, similar to the gender subgroups.

"Division of joint capsule, ligament, or cartilage,

Table 6: Procedures performed on either patients aged below 40 or patients aged between 40 and 60.

Procedure	**Age Below 40**	**Age Between 40 and 60**
Drainage of Right Shoulder Joint, Percutaneous Approach, Diagnostic		✓
Excision of Left Shoulder Bursa and Ligament, Percutaneous Endoscopic Approach	✓	
Excision of Right Shoulder Joint, Percutaneous Endoscopic Approach		✓
Magnetic resonance imaging of other and unspecified sites		✓
Other total shoulder replacement		✓
Repair of recurrent dislocation of shoulder		✓
Repair Right Shoulder Tendon, Open Approach		✓
Rotator cuff repair		✓

Table 7: Statistics for the comparison of the care paths between patients aged above 60 and patients aged between 40 and 60.

	Percentage of Elements	**Number of Elements**
Matched elements	34%	30
Deleted elements *	27%	24
Added elements *	39%	34

* Refer to table 8 for the differences in elements

Table 8: Procedures performed on either patients aged above 60 or patients aged between 40 and 60.

Procedure	**Age Between 40 and 60**	**Age Above 60**
Drainage of Right Shoulder Joint, Percutaneous Approach, Diagnostic	✓	
Excision of Right Shoulder Joint, Percutaneous Endoscopic Approach	✓	
Injection of steroid		✓
Magnetic resonance imaging of other and unspecified sites	✓	
Other arthrotomy, shoulder	✓	
Other total shoulder replacement	✓	
Repair of recurrent dislocation of shoulder	✓	
Repair Right Shoulder Joint, Percutaneous Endoscopic Approach	✓	
Replacement of Right Shoulder Joint with Reverse Ball and Socket Synthetic Substitute, Open Approach		✓
Skeletal x-ray of shoulder and upper arm		✓

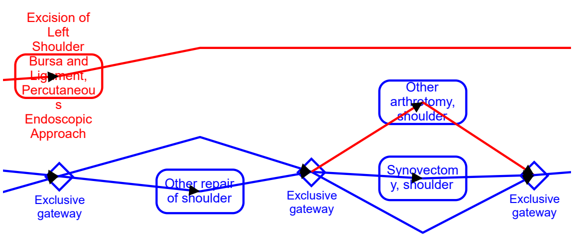

Figure 3: Snapshot of the BPMN diagram for FS patients aged below 40.

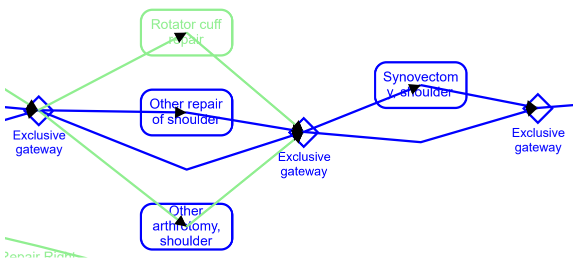

Figure 4: Snapshot of the BPMN diagram for FS patients aged between 40 and 60.

shoulder" is optional for patients aged 60 and above and can be performed in parallel with "Synovectomy, shoulder". In patients aged 40–60, these procedures occur sequentially. This is detailed in Figures 5 and Figure 6.

Figure 5 and Figure 6 show that "Synovectomy, shoulder" is sequential with "Rotator cuff repair" for patients aged 40–60 but exclusive for those aged 60 and above. This exclusivity also applies to "Other repair of shoulder" and "Arthroscopy, shoulder" in rela-

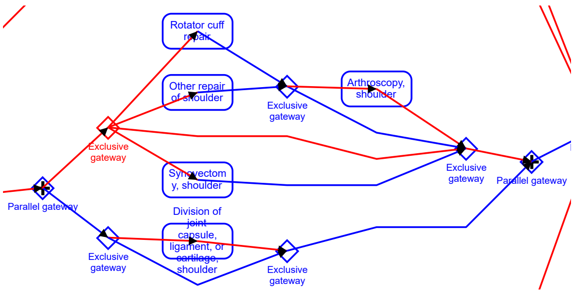

Figure 5: Snapshot of the BPMN diagram for FS patients aged above 60.

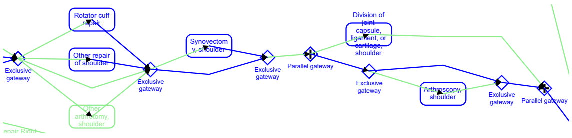

Figure 6: Snapshot of the BPMN diagram for FS patients aged between 40 and 60.

tion to "Synovectomy, shoulder".

After comparison, we conclude that common paths emerge in the progression of a particular disease. In our study of FS, the start and end points of the process are similar across many subpopulations.

5 DISCUSSION

This section discusses the implications of our study's findings and examines the methodological strengths and limitations of our analysis.

5.1 Implications of Findings

The analysis of FS treatment procedures reveals variations that can be explored through a subpopulation-based approach. By incorporating evaluations from patients, public resources, and providers, our study identifies demographic patterns and potential areas for process improvement.

Background research highlights a scarcity of scientific literature specifically addressing FS treatment processes, likely due to the gap between clinical research and applied practice, which can take up to 17 years to bridge (Robinson et al., 2020). To mitigate this delay, practice-based research conducted by clinicians can serve as a crucial link between evidence-based findings and real-world applications (Westfall et al., 2007).

To enrich our analysis, we consulted experienced physiotherapists to reflect on our findings. Their insights underscored distinct demographic patterns in FS patient populations and treatment outcomes. Approximately 70% of FS patients are female, possibly reflecting a tendency among women to seek treatment earlier than men. Although gender does not markedly alter care paths, age significantly influences treatment choices. FS predominantly affects individuals between 40 and 60 years old, with older patients (60+) more likely to develop FS following shoulder trauma and often less inclined toward surgical interventions due to associated risks.

Regional differences in FS treatment approaches were also observed. Patients may opt for hospitals over physiotherapy clinics for broader care options and perceived treatment comprehensiveness. The psychological aspects of FS play a key role, as maintaining a positive mindset has been associated with improved recovery and increased patient adherence to necessary movement protocols.

For FS diagnosis, reliance on imaging alone is often insufficient. While MRI is favored over X-rays for assessing capsule thickness, FS diagnosis typically requires confirmation of a reduction in shoulder mobility exceeding 50%. The discussed subpopulation approach can support more accurate diagnoses by reducing the likelihood of false positives that arise from mismatches between patient-reported symptoms and imaging findings.

5.2 Methodological Strengths and Limitations

Our study adopts a research-oriented methodology focusing on FS treatment, contrasting with the approach presented in (Rademaker et al., 2024), as detailed in Table 9. Our process begins with an exploration of FS techniques to identify relevant attributes within the dataset, followed by the involvement of actual stakeholders, such as physiotherapists in the Netherlands, to ensure that our approach aligns with practical observations and needs. This collaboration with domain experts emphasizes the importance of integrating clinical expertise into the research.

In contrast, (Rademaker et al., 2024) adopts a more data-driven approach, emphasizing data selection, cleaning, and preparation for analysis using process mining tools like ProM. Their study centers on extracting actionable insights from the data itself, with a particular focus on using the "Inductive Visual Miner" for process mining. While they also incorporate literature research to identify relevant attributes and subpopulations, their primary goal is to analyze the data to improve the healthcare process without specific stakeholder engagement.

Our study's strengths include the integration of domain expertise, which enhances the practical rel-

Table 9: Comparison of studies.

	This Paper	**(Rademaker et al., 2024)**
Planning	Defines subgroups based on age and gender for FS cases in MIMIC-IV; includes literature review for background.	Selects general healthcare process (sepsis treatment); defines research goals, metrics, and tools; emphasizes scope and comparison metrics.
Extraction	Extracts FS-specific diagnostic and procedural data using ICD codes; creates subgroup datasets for ProM.	Focuses on cleaning and preparing sepsis data from ER admissions; excludes irrelevant information.
Processing	Organizes data in CSV format, imports into ProM, converts to XES; uses visual plugins and log filters; emphasizes case and event counts.	Employs iterative analysis with event aggregation, filtering, and log enrichment; uses dotted charts; imports data as XES into ProM for further filtering and subpopulation analysis.
Subpopulation Selection	Integrated during data extraction based on age and gender; no separate phase specified.	Dedicated phase with literature research; segments data using attributes like age and severity; utilizes data cubes and the "LogVisualiser" plugin for analysis.
Mining and Analysis	Uses ProM plugins: Inductive Visual Miner, Inductive Miner for Petri Nets; converts to BPMN diagrams; focuses on model fitness.	Uses Inductive Visual Miner; identifies resource usage, paths, and bottlenecks; emphasizes performance and conformance analysis.
Evaluation	Translates insights into actionable suggestions for FS care improvement.	Provides suggestions for future sepsis studies; aims to offer best practices for stakeholders.
Improvement and Support	Collaborates with stakeholders (physiotherapist) to discuss implementing findings.	Outlines future research plan; suggests methodology for guiding subsequent studies.

evance of our findings. By involving physiotherapists in the analysis and interpretation of the data, we ensure that the insights are informed by clinical reality and are more likely to be insightful for practice. Additionally, our focus on a specific condition of FS, allows for a detailed examination of treatment pathways and demographic variations.

6 CONCLUSION

This paper presents a validated methodology for subpopulation analysis in healthcare using process mining techniques, demonstrated through the analysis of care pathways for frozen shoulder patients within the MIMIC-IV dataset. By focusing on gender and age demographics, our analysis suggests categorizing patients into subgroups—males versus females and age groups below 40, between 40 and 60, and above 60—to reveal demographic-driven variations in care paths.

The subpopulation process comparison revealed differences, as indicated by the highest GED of 167 between male and female FS care paths, followed by a GED of 166 between patients aged above 60 and those aged 40–60, and 135 between patients aged below 40 and those aged 40–60. These findings show the role of demographic factors in shaping healthcare delivery, offering actionable insights for personalized interventions. For example, the substantial GEDs suggest that male and female patients, as well as older and younger populations, may benefit from tailored treatment protocols. However, the clinical implications of these variations require further contextualization through diverse stakeholder engagement and deeper analysis of causal factors.

This study contributes to the field of process mining by (i) applying PM^2HC for subpopulation analysis, and (ii) demonstrating how demographic stratification can uncover inefficiencies and inform targeted interventions in healthcare. Despite its contributions, the study is limited by the use of data from a single ICU and the inherent constraints of the MIMIC-IV dataset, which restricts the generalizability of findings and precise attribution of procedures to FS treatment. Future research should address these limitations by incorporating multi-institutional datasets, refining methods to disentangle treatment-specific procedures, and expanding the methodology to other diseases. Future studies on the evaluation of PM^2HC for subpopulation analysis are needed to advance the scientific body of knowledge.

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REFERENCES

Alrawabdeh, J., Alzu'bi, M., Alzyoud, M., Odeh, N., Hamadneh, Y., Mian, H., Mohyuddin, G. R., Kelkar, A. H., Goodman, A. M., Chakraborty, R., Russler-Germain, D. A., Mehra, N., Baggio, D., Cliff, E. R. S., and Al Hadidi, S. (2023). Characteristics of post hoc subgroup analyses of oncology clinical trials: a systematic review. *JNCI Cancer Spectrum*, 7(6):pkad100.

Amatya, A. K., Fiero, M. H., Bloomquist, E. W., Sinha, A. K., Lemery, S. J., Singh, H., Ibrahim, A., Donoghue, M., Fashoyin-Aje, L. A., de Claro, R. A., Gormley, N. J., Amiri-Kordestani, L., Sridhara, R., Theoret, M. R., Kluetz, P. G., Pazdur, R., Beaver, J. A., and Tang, S. (2021). Subgroup analyses in oncology trials: Regulatory considerations and case examples. *Clinical Cancer Research*, 27(21):5753–5756.

Aspland, E., Gartner, D., and Harper, P. (2021). Clinical pathway modelling: a literature review. *Health Systems*, 10(1):1–23.

Becker, A.-K., Dörr, M., Felix, S. B., Frost, F., Grabe, H. J., Lerch, M. M., Nauck, M., Völker, U., Völzke, H., and Kaderali, L. (2021). From heterogeneous healthcare data to disease-specific biomarker networks: A hierarchical bayesian network approach. *PLoS computational biology*, 17(2):e1008735.

Bogarín, A., Cerezo, R., and Romero, C. (2018). Discovering learning processes using inductive miner: A case study with learning management systems (lmss). *Psicothema*, 30:322–329.

Campbell, S. K. (2013). Use of care paths to improve patient management. *Physical & Occupational Therapy in Pediatrics*, 33(1):27–38.

Chen, R. J., Wang, J. J., Williamson, D. F., Chen, T. Y., Lipkova, J., Lu, M. Y., Sahai, S., and Mahmood, F. (2023). Algorithmic fairness in artificial intelligence for medicine and healthcare. *Nature Biomedical Engineering*, 7(6):719–742.

Dasaradharami Reddy, K. and Gadekallu, T. R. (2023). A comprehensive survey on federated learning techniques for healthcare informatics. *Computational Intelligence and Neuroscience*, 2023(1):8393990.

de Boer, T. R., Arntzen, R. J., Bekker, R., Buurman, B. M., Willems, H. C., and van der Mei, R. D. (2024). Process mining on national health care data for the discovery of patient journeys of older adults. *Journal of the American Medical Directors Association*, page 105333.

D'Orsi, G. M., Via, A. G., Frizziero, A., and Oliva, F. (2012). Treatment of adhesive capsulitis: A review. *Muscles, ligaments and tendons journal*, 2(2):70–78.

Evans-Lacko, S., Jarrett, M., McCrone, P., and Thornicroft, G. (2010). Facilitators and barriers to implementing clinical care pathways. *BMC Health Services Research*, 10:1–6.

Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P., Mark, R., Mietus, J., Moody, G., Peng, C., and Stanley, H. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *circulation*, 101(23):e215–e220.

Gonzalez, R. A. and Sol, H. G. (2012). Validation and design science research in information systems. In *Research methodologies, innovations and philosophies in software systems engineering and information systems*, pages 403–426. IGI Global.

Guo, C. and Chen, J. (2023). Big data analytics in healthcare. In *Knowledge technology and systems: Toward establishing knowledge systems science*, pages 27–70. Springer.

Guzzo, A., Rullo, A., and Vocaturo, E. (2022). Process mining applications in the healthcare domain: A comprehensive review. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 12(2):e1442.

Huang, Z., Lu, X., Duan, H., and Fan, W. (2013). Summarizing clinical pathways from event logs. *Journal of Biomedical Informatics*, 46(1):111–127.

Ivanov, S. Y., Kalenkova, A. A., and Aalst, W. M. P. (2015). BPMNDiffViz: A tool for BPMN models comparison. 1418:35–39.

Johnson, A., Bulgarelli, L., Pollard, T., Horng, S., Celi, L. A., and Mark, R. (2021). MIMIC-IV (version 1.0).

Johnson, A. E., Bulgarelli, L., Shen, L., Gayles, A., Shammout, A., Horng, S., Pollard, T. J., Hao, S., Moody, B., Gow, B., et al. (2023). Mimic-iv, a freely accessible electronic health record dataset. *Scientific Data*, 10(1):1.

Koorevaar, R., Riet, E., Ipskamp, M., and Bulstra, S. (2017). Incidence and prognostic factors for postoperative frozen shoulder after shoulder surgery: A prospective cohort study. *Archives of Orthopaedic and Trauma Surgery*, 137.

Ma, F., Ye, M., Luo, J., Xiao, C., and Sun, J. (2021). Advances in mining heterogeneous healthcare data. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 4050–4051.

Mans, R. S., Schonenberg, M. H., Song, M., van der Aalst, W. M. P., and Bakker, P. J. M. (2009). Application of process mining in healthcare–a case study in a dutch hospital. In *Biomedical Engineering Systems and Technologies*, pages 425–438. Springer.

Mena-del Horno, S., Dueñas, L., Lluch, E., Louw, A., Luque-Suarez, A., Mertens, M. G., Fuentes-Aparicio, L., and Balasch-Bernat, M. (2022). A central nervous system focused treatment program for people with frozen shoulder: A feasibility study. *International Journal of Environmental Research and Public Health*, 19(5).

Neame, M. T., Chacko, J., Surace, A. E., Sinha, I. P., and Hawcutt, D. B. (2019). A systematic review of the effects of implementing clinical pathways supported by health information technologies. *Journal of the American Medical Informatics Association*, 26(4):356–363.

Neviaser, A. S. and Hannafin, J. A. (2010). Adhesive capsulitis: A review of current treatment. *The American Journal of Sports Medicine*, 38(11):2346–2356.

Partington, A., Wynn, M., Suriadi, S., Ouyang, C., and Karnon, J. (2015). Process mining for clinical processes: A comparative analysis of four Australian hospitals. *ACM Transactions on Management Information Systems (TMIS)*, 5(4):1–18.

Pereira, G., Santos, E., and Maceno, M. (2020). Process mining project methodology in healthcare: A case study in a tertiary hospital. *Network Modeling Analysis in Health Informatics and Bioinformatics*, 9.

Rababah, E. M., Abu Tariah, H., Halalsheha, R., and Abo Kebar, M. (2020). Frozen shoulder: Pathogenesis, diagnosis and treatment. *Journal of Kerman University of Medical Sciences*, 27(5):447–455.

Rademaker, F. M., Bemthuis, R. H., Jayasinghe, J., and Bukhsh, F. A. (2024). Analyzing sepsis treatment variations in subpopulations with process mining. In *26th International Conference on Enterprise Information Systems*, pages 85–94.

Robinson, T., Bailey, C., Morris, H., Burns, P., Melder, A., Croft, C., Spyridonidis, D., Bismantara, H., Skouteris, H., and Teede, H. (2020). Bridging the research-practice gap in healthcare: A rapid review of research translation centres in England and Australia. *Health research policy and systems*, 18(117).

Rotter, T., de Jong, R. B., Lacko, S. E., Ronellenfitsch, U., and Kinsman, L. (2019). Clinical pathways as a quality strategy. *Improving Healthcare Quality in Europe*, page 309.

Rotter, T., Kugler, J., Koch, R., Gothe, H., Twork, S., van Oostrum, J. M., and Steyerberg, E. W. (2008). A systematic review and meta-analysis of the effects of clinical pathways on length of stay, hospital costs and patient outcomes. *BMC Health Services Research*, 8:1–15.

Scholte, M., Heidkamp, J., Hannink, G., Merkx, M. A. W. T., Grutters, J. P. C., and Rovers, M. M. (2023). Care pathway analysis to inform the earliest stages of technology development: scoping oncological indications in need of innovation. *Value in Health*, 26(12):1744–1753.

Skobtsov, A. and Kalenkova, A. (2019). Efficient algorithms for finding differences between process models. In *2019 Ivannikov Ispras Open Conference (ISPRAS)*, pages 60–66.

Sohail, S. A., Bukhsh, F. A., and van Keulen, M. (2021). Multilevel privacy assurance evaluation of healthcare metadata. *Applied Sciences*, 11(22):10686.

Valero-Ramon, Z., Fernandez-Llatas, C., Valdivieso, B., and Traver, V. (2020). Dynamic models supporting personalised chronic disease management through healthcare sensors with interactive process mining. *Sensors*, 20(18):5330.

van der Aalst, W. M. P. (2011). *Process mining: discovery, conformance and enhancement of business processes*, volume 2. Springer.

van der Aalst, W. M. P. (2016). *Data science in action*. Springer.

Vanhaecht, K., Bollmann, M., Bower, K., Gallagher, C., Gardini, A., Guezo, J., Jansen, U., Massoud, R., Moody, K., Sermeus, W., et al. (2006). Prevalence and use of clinical pathways in 23 countries–an international survey by the European Pathway Association. *Journal of Integrated Care Pathways*, 10(1):28–34.

West, B. T., Berglund, P., and Heeringa, S. G. (2008). A closer examination of subpopulation analysis of complex-sample survey data. *The Stata Journal*, 8(4):520–531.

Westfall, J. M., Mold, J., and Fagnan, L. (2007). Practice-Based Research—"Blue Highways" on the NIH Roadmap. *JAMA*, 297(4):403–406.

Wieringa, R. and Moralı, A. (2012). Technical action research as a validation method in information systems design science. In *International Conference on Design Science Research in Information Systems*, pages 220–238. Springer.

Zreik, N. H., Malik, R. A., and Charalambous, C. P. (2016). Adhesive capsulitis of the shoulder and diabetes: A meta-analysis of prevalence. *Muscles, ligaments and tendons journal*, 6(1):26–34.