Unlocking Nursing Work Organization Insights through Integrated HIS and RTLS Data: Novel Methods and Applications

Haroon Tharwat[1,2,*]

[1]UHasselt – Hasselt University, Faculty of Business Economics, Agoralaan, 3590 Diepenbeek, Belgium
[2]UHasselt – Hasselt University, Digital Future Lab, Agoralaan, 3590 Diepenbeek, Belgium

Abstract

Hospital nursing shortages can lead to significant drawbacks for both patients and nurses, including longer waiting times, missed assessments, delayed responses, and medication errors. Nurses also experience higher stress, increased burnout, and lower job satisfaction. Addressing these challenges requires a deeper understanding of how nursing work is organized in practice. Currently, most insights rely on nurses recording tasks in a Hospital Information System (HIS). While HIS data is context-rich, it is prone to bias and often fails to capture the timing and completeness of nursing activities due to delayed or missing documentation. In contrast, Real-Time Location System (RTLS) data provides an automatically recorded, accurate account of staff and equipment movement, but lacks clinical context and cannot specify the nature of the tasks performed. To date, most research has considered HIS and RTLS data in isolation, limiting the ability to reconstruct a more accurate view of nursing work organization. This doctoral research aims to address this gap by integrating HIS and RTLS data to generate a richer and more accurate nursing task log than either source can provide alone. By combining the strengths of both data types, the resulting unified log serves as a foundation for advanced process mining and analysis, supporting the discovery of actionable insights to improve nursing work organization.

Keywords

Process Mining, Healthcare, HIS data, RTLS data, Nurses, Work Organization

1. Introduction

Hospitals worldwide continually face the complex challenge of delivering high-quality care amidst severe nurse understaffing and rising healthcare demands due to aging populations and global health crises [1, 2, 3]. Nursing staff shortages exacerbate critical issues, including prolonged patient wait times, increased risk of medical errors, and elevated stress and burnout rates among nurses, ultimately diminishing patient care quality and workforce satisfaction [4, 5].

Accurate insights into nursing work organization can help address these challenges by improving resource allocation, workload distribution, and task coordination [6, 7]. Traditional methods for capturing nursing work organization data (eg., diary keeping and observational studies) offer contextual richness but suffer from significant limitations: they are labor-intensive, susceptible to bias (e.g., the Hawthorne effect), and typically constrained by incomplete data collection. Incomplete data collection refers to the fact that not all activities are recorded, key contextual details may be missed, and documentation is often performed later rather than in real time [8, 9, 3, 2].

A commonly used alternative to manual observation is to leverage Hospital Information System (HIS) data. HIS data is generated as part of routine hospital operations and consists of entries documented by healthcare staff during clinical work, resulting in event logs that contain information about activities performed, the patient involved, responsible staff, and the time of registration [4]. However, similarly to traditional methods for capturing nursing work organization data, HIS recordings often exhibit inaccuracies due to delayed entries, batch documentation practices, and omitted tasks, resulting in fragmented and temporally imprecise data [10, 11, 4, 12].

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*Corresponding author.
haroon.tharwat@uhasselt.be (H. Tharwat)
0009-0004-4903-1040 (H. Tharwat)

In addition to HIS data, Real-Time Location Systems (RTLSs) represent an alternative data source that continuously captures the precise spatial and temporal information of nurses and equipment as they move through the ward. Unlike HIS data, which provides clinical and task-related details, RTLSs data does not indicate what activity is being performed; they only record where and when movement occurs. This absence of explicit clinical context means that inferring specific nursing tasks directly from RTLS data alone is challenging [6, 13].

While both HIS and RTLS data sources have been explored in isolation for process mining in healthcare, each provides a distinct view of nursing work [4]. HIS data contributes to detailed clinical context and task-specific information, but lacks location or precise timing. RTLSs, on the other hand, capture accurate movements and presence information, yet do not capture the types of activities performed. By integrating these two data sources, it becomes possible to obtain a more complete, reliable, and accurate view of nursing work organization than would be achievable by analyzing either data source in isolation [4].

This doctoral research proposes a novel approach to systematically integrate HIS and RTLS data. The integration aims to semi-automatically reconstruct a detailed, unified nursing task log by combining clinical activity data from the HIS with precise timing and location data from the RTLS. This unified nursing log enables the identification and analysis of complex work organization patterns – including when and where multitasking occurs, how nurses collaborate in teams, and how activities are distributed across time and space in the ward [14, 4]. The two fundamental challenges addressed in this research are: (i) developing a robust, semi-automated method for integrating HIS and RTLS data into a nursing task log, and (ii) extracting and visualizing actionable insights from the integrated log to support improvement of nursing work organization [4, 15, 16]. By allowing for a more detailed analysis of the flow of nurses, this research helps identify bottlenecks, reduce inefficiencies, and optimize staff allocation. These practical tools for work organization analysis can directly inform evidence-based management decisions and support continuous improvement in patient care.

2. Related Work

Process mining, a prominent field in Business Process Management (BPM), has increasingly focused on healthcare, leveraging HIS data to analyze clinical work organization and support process improvement [17]. Applications include identifying inefficiencies in care delivery, optimizing resource allocation, improving patient flow, and supporting regulatory compliance [11, 18]. For example, Agostinelli et al.[19] employed process mining to analyze care pathways in an Italian hospital, yielding actionable insights that informed management decisions and led to a reduction in patient abandonment rates. Similarly, Kurniati et al.[20] combined HIS event logs with user access data to examine system usage during chemotherapy treatments, revealing patterns in clinician interactions with digital tools and their impact on care delivery. Comprehensive surveys of healthcare process mining studies [17] consistently reveal key data quality challenges in HIS data. Common issues include missing data, such as absent timestamps, activity labels, or patient identifiers, which can lead to incomplete or fragmented process models [21, 22]. Incorrect or inconsistent entries, such as erroneous timestamps, duplicated events, or mismatched patient journey IDs, often arise from manual entry errors or system integration problems and can mislead analyses [23, 21]. Additionally, imprecise or irrelevant data, such as vague or overlapping timestamps, or system-generated events unrelated to clinical work organization, can further compromise the reliability of process mining results [21]. These limitations underscore the importance of robust data quality management and the use of complementary data sources in healthcare process mining.

To address these HIS data quality limitations, recent research proposes leveraging RTLS data as an alternative or complementary source for process analysis. A growing body of work demonstrates that integrating RTLS data with process mining techniques offers substantial benefits for analyzing and optimizing healthcare work organization. For example, Araghi et al. [24] developed a method for visualizing and diagnosing patient pathways using RTLS data, enabling the extraction of valuable operational insights for healthcare decision-makers. In surgical settings, RTLS-driven process mining has been applied to analyze thousands of patient journeys, optimize perioperative procedures, and reduce inefficiencies, providing clear real-world value [25]. RTLSs enable the automatic and unobtrusive collection of high-resolution location data on patients, staff, and equipment, supporting the reconstruction of detailed care pathways without reliance on manual data entry [26, 25]. Collectively, these studies provide strong evidence that process mining with RTLS data is an effective and practical approach for advancing operational efficiency and quality assurance in healthcare environments. Nevertheless, RTLSs data alone have limitations, notably the lack of information about the specific clinical activities being performed.

While prior research has explored process mining using either HIS or RTLS data in isolation, the systematic integration of these sources remains underexplored, mainly in the BPM literature. For example, Osman et al. [27] investigated the integration of RTLSs with HISs data in an emergency and trauma department, focusing primarily on patient pathways and waiting times, but not on the unique complexities of nursing work organization. Yet, integration is arguably even more essential for nursing, as nurses perform a diverse array of tasks, such as rounds, documentation, and direct patient care, that are often only partially or inconsistently recorded in information systems. Building on this identified gap, Martin (2019) lays the conceptual foundation for this doctoral research by systematically examining both the opportunities and the methodological challenges of combining RTLS and HIS data. Notably, Martin (2019) explicitly calls for practical methods to enable such integration, highlighting the need for innovative approaches tailored to the realities of healthcare practice [4]. This doctoral research directly responds to that call by developing and validating a systematic approach for merging RTLS and HIS data. The resulting unified event log of nursing work enables a more comprehensive analysis of work organization. It supports targeted process optimization, addressing both the challenges outlined and the conceptual vision set out by Martin (2019).

In summary, although previous research has explored process mining with different data sources, there is currently no established method for systematically integrating HIS and RTLS data to reconstruct complete nursing task logs. This research directly addresses this gap by developing and validating a novel, semi-automated footprint-based approach for integrating HIS and RTLS data, thereby enabling more accurate reconstruction and analysis of nursing work organization.

3. Research Objectives

Given the limitations identified in prior literature regarding the accurate reconstruction of nursing work organization from isolated data sources, this doctoral research addresses two primary research objectives:

1. **Integration of HIS and RTLS Data:** Develop a robust, semi-automated approach to integrate heterogeneous data sources (HIS & RTLS) into a unified nursing task log. By overcoming the individual limitations of each source, the integrated log will provide more accurate timestamps, richer clinical context, and precise location information. This integration is essential for reliably reconstructing nursing tasks and activities, which are often incompletely captured in existing systems due to documentation delays, missing data, or sensor inaccuracies.
   This unified log aims to overcome individual limitations by providing more accurate timestamps, context, and location identification.
2. **Work Organization Pattern Analysis and Visualization:** Leverage the unified nursing task log to systematically identify, analyze, and visualize key patterns in the organization of nursing work. The objective is to provide actionable, data-driven insights that support the improvement and optimization of nursing work organization. By revealing complex patterns such as multitasking, collaboration, and temporal-spatial allocation of resources, these analyses aim to inform evidence-based management decisions and support practical improvements in work organization efficiency and patient care.

4. Research Methodology

This doctoral research addresses two primary methodological challenges to achieve its objectives.

4.1. Challenge 1: Robust Integration of HIS and RTLS Data

To more accurately reconstruct nursing work organization, this research is developing and iteratively validating a structured, semi-automated method that leverages domain knowledge to integrate HIS and RTLS data systematically. The input consists of structured HIS records, including task labels, nurse and patient identifiers, and timestamps documenting task completions (e.g., medication administration, vital sign checks), as well as continuous RTLS logs that capture the real-time locations of nurses and medical equipment. The integration process begins by defining task footprints, which translate domain expertise into concrete criteria: specifying which resources must be present, the relevant spatial constraints (e.g., patient rooms), and the required temporal alignment. For example, the task ”Medication Administration” may be operationalized as a nurse and medication cart co-located in the patient's room for a minimum duration, temporally aligned with a corresponding HIS timestamp. A footprint-based matching algorithm then systematically scans the HIS and RTLS data to identify events that satisfy these criteria—extracting relevant HIS entries, filtering RTLS data by nurse identifiers, confirming co-location and temporal overlap within set tolerance windows, and ultimately generating a unified task log enriched with semantic and spatial-temporal detail. The method will be rigorously validated using synthetic data generated from a discrete-event simulation environment, with systematic performance assessment using precision, recall, F1-score, and accuracy. Looking ahead, future iterations will explore more data-driven approaches, including the use of machine learning to detect frequently occurring work organization patterns directly from the integrated data.

4.2. Challenge 2: Analysis and Visualization of Work Organization Patterns

Once a unified nursing task log is generated, advanced process mining techniques and data analytics methods will be applied to reveal underlying work organization patterns. Specific patterns to be explored include multitasking behaviors, inter-nurse collaboration, and temporal distribution of activities. The output will consist of interactive, intuitive visualizations explicitly designed to communicate actionable insights to nurses and hospital administrators. These visualizations will be developed iteratively in collaboration with clinical stakeholders, ensuring relevance, clarity, and practical usability.

5. Preliminary Results

The current stage of this doctoral research focuses on developing, evaluating, and refining a robust data integration pipeline for synthesizing HIS and RTLS data into a nursing task log. Given the practical limitations in obtaining the ground truth in a real-life setting, synthetic data was generated.

5.1. Simulation-based Synthetic Data Generation

A discrete-event simulation model (built using the SimPy framework) was developed to systematically generate realistic synthetic datasets representing nursing tasks in a hospital ward. First, an idealized “ground truth” nursing task log is created, accurately capturing the start and end times of each task, the resources involved (e.g., specific nurses and equipment), patient identifiers, and explicit task labels (e.g., medication administration, vital sign checks). Second, corresponding idealized HIS and RTLS logs are derived from this perfect log, reflecting exact clinical documentation and precise real-time movements with no data quality issues. Third, realistic imperfections typical of actual hospital data are introduced into these logs. Specifically, the HIS logs incorporate delayed documentation (up to 10 minutes) and aggregated or missing entries (10% omission), while the RTLS logs include intermittent signal loss (5% dropout), temporal jitter (±2 minutes), and occasional incorrect nurse location assignments. This structured synthetic data generation approach provides a controlled environment for evaluating and refining the footprint-based integration method.

5.2. Initial Evaluation and Insights

The footprint-based matching algorithm is currently under iterative development. It integrates HIS and RTLS data by leveraging domain-driven task footprints that explicitly encode clinical knowledge into structured definitions (resource requirements, spatial constraints, and temporal alignment criteria). Preliminary evaluations with these synthetic datasets provide controlled benchmarks and valuable feedback that directly inform ongoing methodological refinements.

Initial evaluation results, focusing on standard metrics such as precision, recall, and F1-score, highlight clear strengths and specific areas for improvement. For instance, the algorithm demonstrates promising precision in correctly identifying task matches but faces challenges with recall, underscoring the need for improved sensitivity and robustness against data imperfections. These findings are actively guiding the next development iterations, including adaptive temporal matching techniques and improved handling of RTLS data variability. Moreover, these preliminary insights underscore the value of the structured synthetic approach as both a methodological tool and a guiding mechanism for refining the algorithm toward reliable real-world applicability.

6. Next Steps

These initial findings provide a solid foundation for targeted improvements and validation of the integration approach. Moving forward, the matching algorithm will be refined by incorporating adaptive temporal alignment strategies, enabling more robust identification of nursing tasks despite variable documentation delays and intermittent RTLS signals. The task footprint library will be expanded to represent increasingly complex and collaborative clinical scenarios, ensuring the integration approach remains applicable to real-world nursing workflows. Additionally, the method's robustness to common data imperfections (e.g., missing entries or sensor inaccuracies) will be improved by developing enhanced error-handling logic. All methodological improvements will be thoroughly validated using synthetically generated HIS and RTLS datasets, with performance evaluated through quantitative metrics (e.g., precision, recall, F1-score).

Subsequently, the development of pattern analysis and visualization techniques will commence, utilizing the enriched task log to derive actionable insights into nursing work organization and to design intuitive visual representations for end-users. Through these concrete next steps, this research aims to deliver a scalable and clinically relevant framework for more accurate, data-driven analysis of nursing work organization.

7. Conclusion

This doctoral research proposes a structured, semi-automated approach to integrate HIS and RTLS data for reconstructing unified nursing task logs. By leveraging domain-driven task footprints, the methodology systematically combines complementary sources, addressing common limitations of existing hospital data and enabling a more complete and accurate analysis of nursing work organization. Initial synthetic data evaluations confirm the promise of the approach and highlight specific challenges, particularly in terms of sensitivity to missing and imprecise data. These insights directly inform ongoing development, guiding further algorithmic refinement and comprehensive validation in real-world hospital settings. Ultimately, this work aims to provide a robust methodological foundation for process mining and the optimization of nursing work organization, supporting more effective and data-driven care delivery.

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Declaration on Generative AI

This author has employed Generative AI tools (e.g., ChatGPT) solely for grammar correction and language refinement. No AI-generated text contributed to the scientific content or analysis of the paper.

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