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Research Article

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Posted Date: November 12th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11139419/v1

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Additional Declarations: No competing interests reported.

Characterizing In-Hospital Patient Transport Workflows Using Mobile Application Log Data and Nonnegative Matrix Factorization: A Retrospective Observational Study

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Abstract

Background: In-hospital patient transport is a vulnerable phase of care influenced by multiple clinical and operational factors. Despite its importance, objective, quantitative evidence capturing this workflow complexity remains limited, complicating comprehensive assessment. We analyzed routinely collected logs from a locally developed smartphone application used by dedicated patient transport staff to characterize workflow patterns and examine their associations with transport duration.

Methods: We retrospectively analyzed 5,902,138 transport events at a tertiary referral hospital between 2014 and 2021. Duration was measured from recorded task initiation at the departure

location to recorded completion. Nonnegative matrix factorization (NMF) identified patterns in origin–destination locations and request and initiation times. Peak hours were defined as clock hours with mean transactions per second at or above the 75th percentile, using hospital information system logs from 2025. Multivariable regression included interactions of peak periods with transport modes and workflow topics.

Results: Six topics were identified. The largest primarily represented transport from inpatient wards to procedure and examination rooms (Topic 5; n = 2,384,129; 40.4%). For walking transport in Topic 5, peak periods were associated with a 0.76-min longer duration (95% CI, 0.74–0.79). At non-peak times, bed and cart transport were associated with durations 2.41 and 2.52 min longer than walking, respectively. Peak-period associations varied by topic and transport mode; Topic 1 showed shorter predicted durations during peak periods.

Conclusions: Application logs characterized transport workflows and context-dependent differences in duration. The frequent ward-to-procedure and examination room pattern, with longer predicted durations during peak periods, warrants focused assessment of transport demand and resource allocation.

Keywords: Patient Transport; Hospital Information System; Workflow Analysis; Operations Management; Mobile Application Logs; Nonnegative Matrix Factorization

Background

In-hospital patient transport supports timely access to diagnostic and therapeutic services and requires coordination across hospital departments [1-4]. The transport process is inherently complex, consisting of multiple stages—request, assignment, movement, and arrival—that require interdepartmental handoffs and communication [5, 6]. This inherent complexity is further compounded by the reliance on finite resources, such as dedicated personnel, specialized equipment, and available space [7]. Variations in transport demand and available resources can influence waiting

and task completion times [9, 15, 16, 22]. Patient transport also imposes physical and ergonomic demands on transport personnel, making workload distribution an important operational consideration [11, 12]. Consequently, the workload of frontline healthcare providers may increase, potentially compromising the overall quality of care [11, 12]. Therefore, it is essential to establish a framework that systematically monitors, identifies, and shares data on when and how patient transport delays occur [1, 8].

Previous research has examined patient transport through empirical workflow evaluation, simulation, and optimization, with some studies combining these approaches [1, 2, 10, 15–17, 22]. The observational stream focuses on characterizing in-hospital transport delays by identifying associated operational factors within hospital workflows, including human and material resources, as well as patients' clinical characteristics [13, 14]. In contrast, the optimization stream aims to actively resolve these inefficiencies. To achieve this, optimization research focuses on designing discrete-event simulation and algorithm-based dispatch strategies that leverage patient acuity and spatial characteristics to minimize wait times [1, 2, 15, 16]. Collectively, the complementary findings from both research streams suggest that multiple operational elements—including time, space, patient acuity, and resource availability—are critical determinants of patient transport performance.

Although both observational and optimization studies have provided important insights into understanding and improving patient transport delays, a gap remains between these two approaches. Specifically, observational studies have primarily focused on the independent effects of individual variables, often failing to capture the complex interactions among multiple operational factors that drive bottlenecks [10, 17-20]. In contrast, optimization studies frequently rely on simplifying assumptions about transport processes and resource availability, resulting in limited explanatory power regarding the dynamic and multifactor nature of real-world hospital operations [1, 21, 22]. As a result, approaches are needed that bridge the gap by capturing real-world, context-specific interactions and integrating them into analytical frameworks that can inform optimization-based strategies.

To this end, we propose a context-centered analytical framework to better represent the structural dynamics underlying transport delays in clinical practice. This approach utilized over 5 million real-world operational log records collected from a patient transport management application in a tertiary care hospital. Instead of treating variables independently, we modeled transport processes as context-specific combinations of multiple operational factors. Non-negative matrix factorization (NMF) was applied to translate complex, interrelated transport data into meaningful latent patterns, providing a clearer lens to understand the operational context [23-25]. We then incorporated these patterns into a statistical framework to examine interaction effects between transport contexts and key operational variables, including peak times and transport modes. Taken together, this framework provides an interpretable basis for deciphering real-world transport complexity, allowing context-specific bottlenecks to be identified and operational strategies to be refined for more efficient in-hospital transport.

Methods

Data Collection

We conducted a retrospective observational study using routinely collected logs from a smartphone application used by dedicated patient transport staff at a tertiary referral hospital from 2014 to 2021. The application supported transport assignment and workflow documentation. Data were extracted in collaboration with the hospital's information technology department.

The log data consisted of event-based records documenting workflow processes for individual transport cases. A transport event was defined as a single patient transfer between clearly identified origin and destination locations. All records associated with a transport identifier were excluded if that identifier encompassed two or more transport legs, such as a transfer from a ward to an examination room followed by onward transport to another location. Individual log records represented recorded

workflow steps. Records sharing a unique transport identifier were linked to reconstruct a transport event, which constituted the unit of analysis.

Ten features were extracted (Table 1), including patient and transport identifiers, task types, transport status, transport modes, departure and arrival locations, and timestamps for both transport requests and task execution. Transport modes were categorized as walking (WLK), bed (BED), stretcher cart (CART), and wheelchair (WC). Locations were categorized as emergency room (ER), intensive care unit (ICU), operating room (OR), inpatient ward (WD), outpatient department (OPD), procedure and examination room (PROC), and other locations (OTL). To examine whether transport duration varied with hospital activity, we additionally analyzed hospital information system transaction logs collected from July 1 to August 9, 2025. Transaction rates, expressed as transactions per second (TPS), were used as a proxy for hospital-wide activity. Peak periods were defined as hours with TPS values at or above the 75th percentile.

Table 1. Variables extracted from patient transport application logs.

Variable	Description, Categories/Values	Included in NMF[a]
Transport task	Transport confirmation, Transport completion processing, Transport information (request/cancel/complete), Departure location arrival, Delay reason entry, Others	No
Transport status	Completed, Assignment canceled, Requested, Called, Delayed	No
Transport mode	Walking, Bed, Stretcher cart, Wheelchair	No
Task date time	Timestamp at which transport staff logged “Departure location arrival” in the application, indicating the start of the transport task: Morning (06:00-11:59), Afternoon (12:00-17:59), Other (18:00-05:59)	Yes
Request date time	Timestamp at which a ward nurse or examination room staff member requested patient transport through the transport management system: Morning (06:00-11:59), Afternoon (12:00-17:59), Other (18:00-05:59)	Yes
Transport	Elapsed time, in minutes, from the “Departure location arrival”	No

duration	timestamp to the "Transport information (complete)" timestamp.	
Waiting time	Elapsed time, in minutes, from request submission (Request date time) to recorded task initiation (Task date time), used to assess the timeliness of task initiation following a transport request.	No
Departure location	The starting point for the patient being transported: Emergency room, Intensive care unit, Operating room, Inpatient ward, Outpatient department, Procedure and examination room, Other locations.	Yes
Arrival location	The destination for the patient being transported: Emergency room, Intensive care unit, Operating room, Inpatient ward, Outpatient department, Procedure and examination room, Other locations.	Yes

[a]NMF: non-negative matrix factorization.

Case Inclusion

Data selection and quality control processes are shown in Fig 1. From the 9,637,173 initial logs (2014–2021), we excluded cases with timestamp errors, duplicates, or missing logs, retaining 7,967,655 events. Further exclusions for irregular task steps or missing timestamps resulted in 7,458,679 cases with calculable durations. After removing duration outliers (upper/lower 5%), non-standard transport modes, and off-hour events (before 6:00 AM or after 6:59 PM), the final dataset comprised 5,902,138 events for NMF analysis and regression modeling.

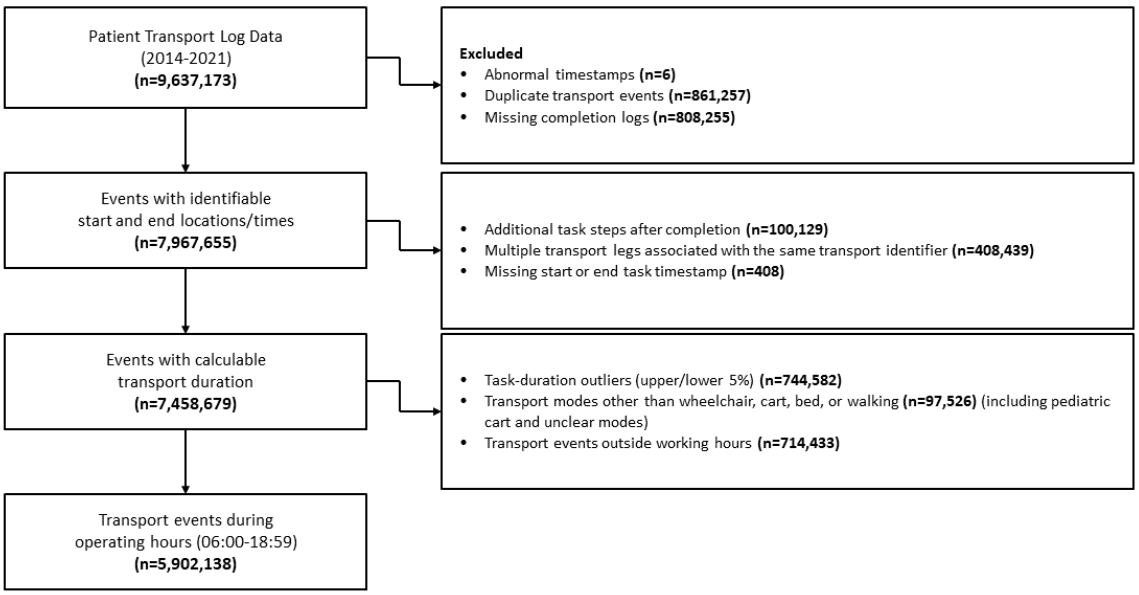


Fig. 1 Flow diagram of log inclusion and exclusion.

Topic Modeling Using NMF

We employed NMF to identify latent transport patterns within hospital patient transport log data (Fig 2) [25]. NMF decomposes a high-dimensional non-negative input matrix X into two factor matrices: a transport event-by-topic matrix (W) and a topic-by-feature matrix (H).

We constructed the input matrix X using categorical variables from Task date time, Request date time, Departure location, and Arrival location (Table 1). Each transport event (row) is represented as a weighted combination of latent topics, where each topic is defined by a distinct pattern of variable combinations.

To select the number of topics, NMF models with different values of K (4–10) were compared using the mean entropy of the event-level topic weight distributions. Lower mean entropy indicated more concentrated topic weights within individual transport events [26]. Mean entropy was 0.86 at K=4, 1.13 at K=5, 0.75 at K=6, 1.33 at K=7, 1.30 at K=8, 1.35 at K=9, and 1.60 at K=10 (Additional file 1: Fig. S1); the model with the lowest mean entropy (K=6) was selected for subsequent analyses. The model was implemented using scikit-learn in Python [27]. The resulting topics were interpreted based

on feature weights in matrix H, revealing distinct location-time patterns that were subsequently incorporated into regression models to examine their effects on transport duration (Fig 2).

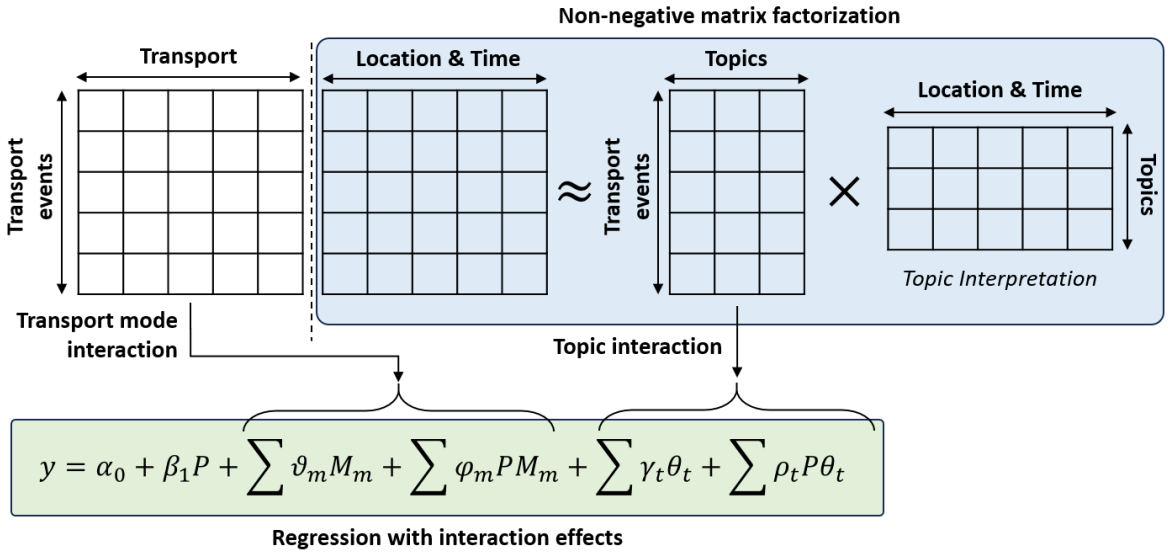


Fig. 2 Non-negative matrix factorization and regression model framework.

Transport location and time variables were decomposed into latent topic patterns using non-negative matrix factorization, and the resulting topic variables were included in a regression model with peak time and transport-mode interaction terms. Variables indicate: y, transport duration; P, peak time indicator; θ_t, NMF-derived topic variables (t=1-5); M_m, transport mode dummy variables (m=1-3); $P\theta_t$ and PM_m, interaction terms between peak time and topics or transport modes.

Regression Analysis

To identify factors associated with transport duration, we conducted regression analysis (Fig 2). The dependent variable was transport duration, calculated in minutes as the difference between departure and arrival times. Independent variables included (1) peak time indicator, (2) transport mode, and (3) NMF-derived topics.

To examine factors affecting transport duration, we constructed an interaction regression model incorporating peak time, transport mode, and NMF topics. We included peak time × transport mode and peak time × topic interaction terms to account for potential differential effects of peak times across transport modes and patterns (Fig 2). The model was estimated using the statsmodels library in Python [28]. Given the large sample size, interpretation focused on coefficient estimates and 95% CIs rather than statistical significance alone.

Results

Characteristics of Transport Events

Applying the TPS-based criterion identified 09:00–11:59 and 13:00–15:59 as peak periods. The final dataset included 5,902,138 transport events, of which 3,420,891 (58.0%) occurred during peak periods and 2,481,247 (42.0%) during non-peak periods. The unadjusted mean transport duration was 11.17 min during peak periods and 10.24 min during non-peak periods, a difference of 0.93 min. Cart transport accounted for a larger proportion of events during peak periods than during non-peak periods (27.4% vs. 21.6%; Table 2).

Table 2. Characteristics of patient transport events by peak versus non-peak time.

Variables (%)	Peak (n = 3420891)	Non-peak (n = 2481247)	Total (n = 5902138)	*P* value
Transport Duration Mean (SD), min	11.17 (4.39)	10.24 (4.19)	10.78 (4.33)	< .001
Waiting Time Mean (SD), min	348.45 (346.57)	354.64 (364.21)	351.05 (354.11)	< .001
Transport Mode[a]				< .001
WLK	335793 (9.8)	238669 (9.6)	574462 (9.7)	
BED	425175 (12.4)	346023 (13.9)	771198 (13.1)	
CART	937278 (27.4)	535953 (21.6)	1473231 (25.0)	

WC	1722645 (50.4)	1360602 (54.8)	3083247 (52.2)	
Departure Location[b]				< .001
ER	151172 (4.4)	124671 (5.0)	275843 (4.7)	
ICU	7805 (0.2)	4187 (0.2)	11992 (0.2)	
OR	12092 (0.4)	9416 (0.4)	21508 (0.4)	
PROC	1351797 (39.5)	996942 (40.2)	2348739 (39.8)	
WD	1826381 (53.4)	1310148 (52.8)	3136529 (53.1)	
OPD	66821 (2.0)	30220 (1.2)	97041 (1.6)	
OTL	4823 (0.1)	5663 (0.2)	10486 (0.2)	
Arrival Location[b]				< .001
ER	94003 (2.7)	79647 (3.2)	173650 (2.9)	
ICU	7129 (0.2)	5143 (0.2)	12272 (0.2)	
OR	149854 (4.4)	137282 (5.5)	287136 (4.9)	
PROC	1850896 (54.1)	1290893 (52.0)	3141789 (53.2)	
WD	1163980 (34.0)	918760 (37.0)	2082740 (35.3)	
OPD	142285 (4.2)	47020 (1.9)	189305 (3.2)	
OTL	12744 (0.4)	2502 (0.1)	15246 (0.3)	
Request Time				< .001
Morning (6:00-11:59)	1024394 (29.9)	460927 (18.6)	1485321 (25.2)	
Afternoon (12:00-17:59)	758111 (22.2)	594178 (23.9)	1352289 (22.9)	
Other (18:00-05:59)	1638386 (47.9)	1426142 (57.5)	3064528 (51.9)	
Task Time				< .001
Morning (6:00-11:59)	1865230 (54.5)	1177546 (47.5)	3042776 (51.6)	
Afternoon (12:00-17:59)	1555661 (45.5)	1100895 (44.4)	2656556 (45.0)	
Other (18:00-05:59)	0 (0.0)	202806 (8.2)	202806 (3.4)	

P values were calculated using the Mann-Whitney U test for continuous variables and the chi-square test for categorical variables. [a]Transport mode abbreviations: WLK, walking; BED, bed; CART, cart; WC, wheelchair. [b]Location abbreviations: ER, emergency room; ICU, intensive care unit; OR, operating room; WD, ward; OPD, outpatient department; PROC, procedure and examination room; OTL, other locations

NMF-Based Transport Patterns

The six-topic model yielded the lowest mean entropy (0.749) and was selected for the final analysis. Topic 5, characterized predominantly by transport from inpatient wards to procedure and examination rooms, was the most frequent topic (n = 2,384,129; 40.4%). Topic 2 was primarily characterized by transport in the opposite direction. Topics 1, 3, 4, and 6 were primarily characterized by temporal features: evening or overnight requests with morning task initiation, afternoon requests and task initiation, morning requests and task initiation, and evening or overnight requests with afternoon task initiation, respectively. Topic 1 accounted for only 1,167 events (0.02%). Topic characteristics are summarized in Fig. 3 and Table 3.

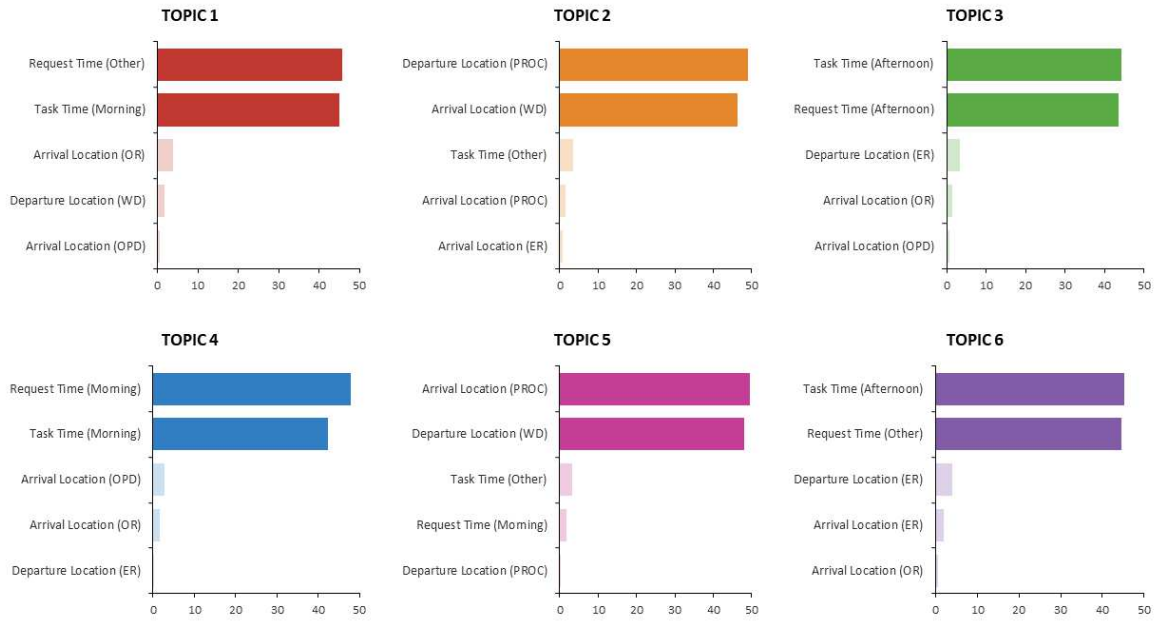


Fig. 3 Top contributing variables for each of the six topics identified by non-negative matrix factorization.

Fig 4 shows topic-level variation in transport duration and waiting time. Topics 2 and 4 generally showed shorter transport duration, whereas Topics 3, 5, and 6 were centered at higher values; Topic 1 showed greater variability.

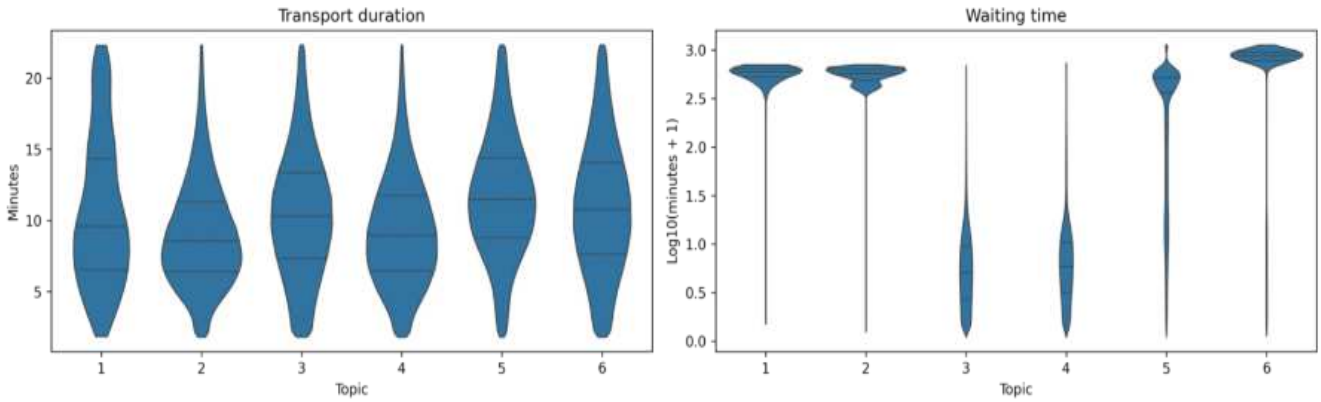


Fig. 4 Distributions of transport duration and waiting time across NMF-derived topics. Transport duration is shown in minutes; waiting time is displayed as log10 (waiting time in minutes + 1).

Table 3. Characteristics of patient transport events by NMF-derived topic.

Variables (%)	**Topic 1 (n = 1167)**	**Topic 2 (n = 462097)**	**Topic 3 (n = 890380)**	**Topic 4 (n = 857268)**	**Topic 5 (n = 2384129)**	**Topic 6 (n = 1307097)**	**Total (n = 5902138)**
Transport Mode[a]							
WLK	107 (9.2)	11618 (2.5)	56200 (6.3)	48965 (5.7)	344522 (14.5)	113050 (8.6)	574462 (9.7)
BED	112 (9.6)	69071 (14.9)	104868 (11.8)	110722 (12.9)	318915 (13.4)	167510 (12.8)	771198 (13.1)
CART	575 (49.3)	76037 (16.5)	359754 (40.4)	199652 (23.3)	428801 (18.0)	408412 (31.2)	1473231 (25.0)
WC	373 (32.0)	305371 (66.1)	369558 (41.5)	497929 (58.1)	1291891 (54.2)	618125 (47.3)	3083247 (52.2)
Departure Location[b]							
ER	492 (42.2)	1870 (0.4)	96218 (10.8)	52692 (6.1)	34170 (1.4)	90401 (6.9)	275843 (4.7)
ICU	170 (14.6)	255 (0.1)	3354 (0.4)	2586 (0.3)	1634 (0.1)	3993 (0.3)	11992 (0.2)
OR	96 (8.2)	3105 (0.7)	3199 (0.4)	3425 (0.4)	56 (0.0)	11627 (0.9)	21508 (0.4)

PROC	0 (0)	443356 (95.9)	629058 (70.7)	656130 (76.5)	48263 (2.0)	571932 (43.8)	2348739 (39.8)
WD	0 (0)	0 (0)	119997 (13.5)	112626 (13.1)	2298062 (96.4)	605844 (46.4)	3136529 (53.1)
OPD	404 (34.6)	11383 (2.5)	34834 (3.9)	28641 (3.3)	1902 (0.1)	19877 (1.5)	97041 (1.6)
OTL	5 (0.4)	2128 (0.5)	3720 (0.4)	1,168 (0.1)	42 (0.0)	3423 (0.3)	10486 (0.2)
Arrival Location[b]							
ER	140 (12.0)	22602 (4.9)	59949 (6.7)	33081 (3.9)	45 (0.0)	57833 (4.4)	173650 (2.9)
ICU	544 (46.6)	1011 (0.2)	4308 (0.5)	2461 (0.3)	232 (0.0)	3716 (0.3)	12272 (0.2)
OR	201 (17.2)	1470 (0.3)	63758 (7.2)	59817 (7.0)	113377 (4.8)	48513 (3.7)	287136 (4.9)
PROC	0 (0.0)	0 (0.0)	161134 (18.1)	130490 (15.2)	2220631 (93.1)	629534 (48.2)	3141789 (53.2)
WD	0 (0.0)	435190 (94.2)	547716 (61.5)	574049 (67.0)	8910 (0.4)	516875 (39.5)	2082740 (35.3)
OPD	272 (23.3)	1703 (0.4)	51140 (5.7)	53889 (6.3)	37115 (1.6)	45186 (3.5)	189305 (3.2)
OTL	10 (0.9)	121 (0.0)	2375 (0.3)	3481 (0.4)	3819 (0.2)	5440 (0.4)	15246 (0.3)
Request Time							
Morning (6:00-11:59)	0 (0.0)	0 (0.0)	0 (0.0)	856029 (99.9)	571646 (24.0)	57646 (4.4)	1485321 (25.2)
Afternoon (12:00-17:59)	0 (0.0)	0 (0.0)	890104 (100)	0 (0.0)	462185 (19.4)	0 (0.0)	1352289 (22.9)
Other (18:00-05:59)	1167 (100)	462097 (100)	276 (0.0)	1239 (0.1)	1350298 (56.6)	1249451 (95.6)	3064528 (51.9)
Task Time							
Morning (6:00-11:59)	1167 (100)	462097 (100)	276 (0.0)	857209 (100)	1720874 (72.2)	1153 (0.1)	3042776 (51.6)
Afternoon (12:00-17:59)	0 (0.0)	0 (0.0)	871072 (97.8)	0 (0.0)	583141 (24.5)	1202343 (92.0)	2656556 (45.0)
Other (18:00-	0	0	19032	59	80114	103601	202806

05:59)	(0.0)	(0.0)	(2.1)	(0.0)	(3.4)	(7.9)	(3.4)
Peak Time							
Peak	895 (76.7)	311440 (67.4)	499829 (56.1)	616546 (71.9)	1306760 (54.8)	685421 (52.4)	3420891 (58.0)
Non-peak	272 (23.3)	150657 (32.6)	390551 (43.9)	240722 (28.1)	1077369 (45.2)	621676 (47.6)	2481247 (42.0)

[a]Transport mode abbreviations: WLK, walking; BED, bed; CART, cart; WC, wheelchair. [b]Location abbreviations: ER, emergency room; ICU, intensive care unit; OR, operating room; WD, ward; OPD, outpatient department; PROC, procedure and examination room; OTL, other locations.

Values are presented as n (%), with percentages calculated within each column.

Multivariable Regression Results

The results of the multivariable regression model are summarized in Table 4. To facilitate interpretation of interaction effects, predicted mean transport duration times are further visualized in Figs 5 and 6.

Table 4. Multivariable regression model for transport duration.

Variables	Coefficient (β)	Standard error	95% CI [lower, upper]	*P* value
Intercept	9.9015	0.009	[9.885, 9.918]	< .001
Peak	0.7629	0.011	[0.741, 0.785]	< .001
Transport mode (ref: WLK)				
BED	2.4101	0.011	[2.389, 2.432]	< .001
CART	2.5238	0.010	[2.504, 2.544]	< .001
WC	0.8855	0.009	[0.867, 0.903]	< .001
Topic (ref: Topic 5)				
Topic 1	-0.1805	0.248	[-0.667, 0.306]	0.467

Topic 2	-3.4444	0.011	[-3.467, -3.422]	< .001
Topic 3	-1.3293	0.008	[-1.345, -1.314]	< .001
Topic 4	-3.2438	0.009	[-3.262, -3.226]	< .001
Topic 6	-1.1677	0.007	[-1.181, -1.155]	< .001
Interaction terms				
Peak time x BED	-0.0294	0.014	[-0.058, -0.001]	0.042
Peak time x CART	0.2654	0.013	[0.239, 0.291]	< .001
Peak time x WC	0.1553	0.012	[0.132, 0.179]	< .001
Peak time x Topic 1	-2.0953	0.283	[-2.650, -1.540]	< .001
Peak time x Topic 2	0.9705	0.014	[0.943, 0.998]	< .001
Peak time x Topic 3	-0.5377	0.010	[-0.558, -0.517]	< .001
Peak time x Topic 4	0.8100	0.011	[0.788, 0.832]	< .001
Peak time x Topic 6	0.4435	0.009	[0.426, 0.461]	< .001

Coefficients are expressed in minutes. The reference category was non-peak walking transport in Topic 5. CI: confidence interval; WLK: walking; BED: bed; CART: cart; WC: wheelchair.

In the regression model, the intercept represents the estimated mean transport duration for the reference condition, defined as non-peak transfers using WLK and classified as Topic 5 (WD to PROC). For walking transport in Topic 5, the model-estimated mean duration was 9.90 min during non-peak periods, with a peak–non-peak difference of 0.763 min (95% CI, 0.741–0.785). During non-peak periods, bed, cart, and wheelchair transport had longer estimated durations than walking transport, with differences of 2.41, 2.52, and 0.89 min, respectively. Topic 2 and Topic 4 had shorter estimated durations than Topic 5 during non-peak periods, with differences of −3.44 and −3.24 min, respectively (Table 4).

Compared with walking transport, the peak–non-peak difference was 0.27 min larger for cart transport, 0.16 min larger for wheelchair transport, and 0.03 min smaller for bed transport. The peak–non-peak difference also varied across topics. For walking transport, the estimated differences were 1.73 min

for Topic 2, 1.57 min for Topic 4, 1.21 min for Topic 6, 0.76 min for Topic 5, 0.23 min for Topic 3, and −1.33 min for Topic 1.

Fig. 5. Model-predicted mean transport duration during peak and non-peak periods. (A) Predictions by topic with transport mode fixed at walking. (B) Predictions by transport mode with topic fixed at Topic 5. Across transport modes, the model-predicted peak–non-peak differences were positive for Topics 2–6 and negative for Topic 1. Differences ranged from 1.70 to 2.00 min for Topic 2, 0.20 to 0.49 min for Topic 3, 1.54 to 1.84 min for Topic 4, 0.73 to 1.03 min for Topic 5, and 1.18 to 1.47 min for Topic 6. For Topic 1, differences ranged from −1.36 to −1.07 min (Fig. 6).

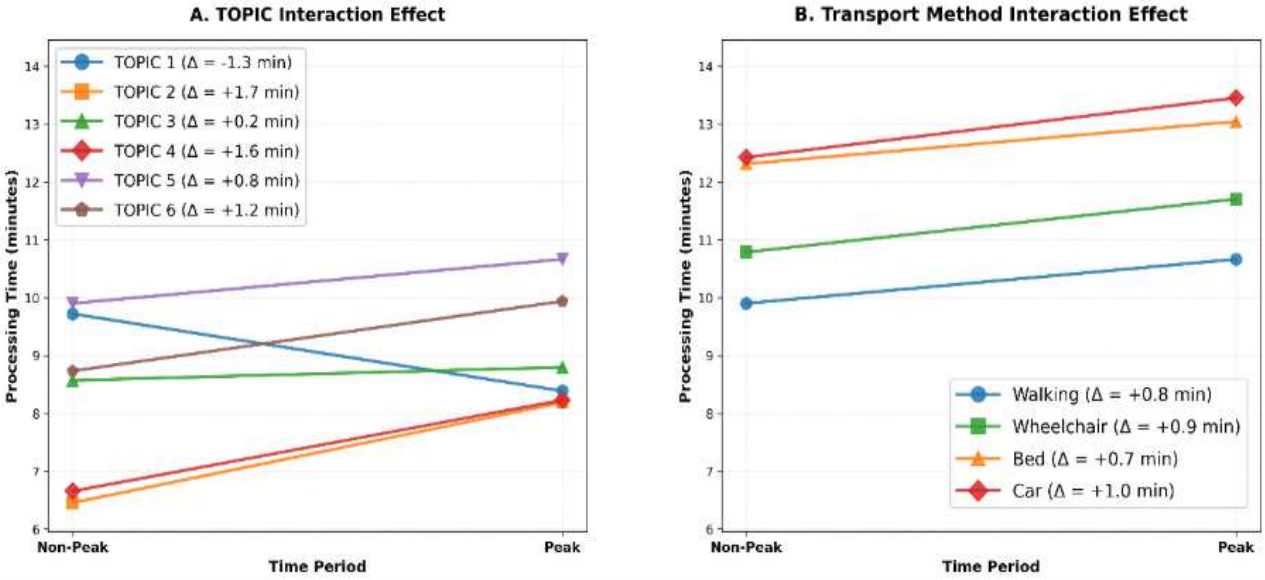


Fig. 5 Interaction effects of peak time with NMF-derived topic and transport mode on predicted transport duration.

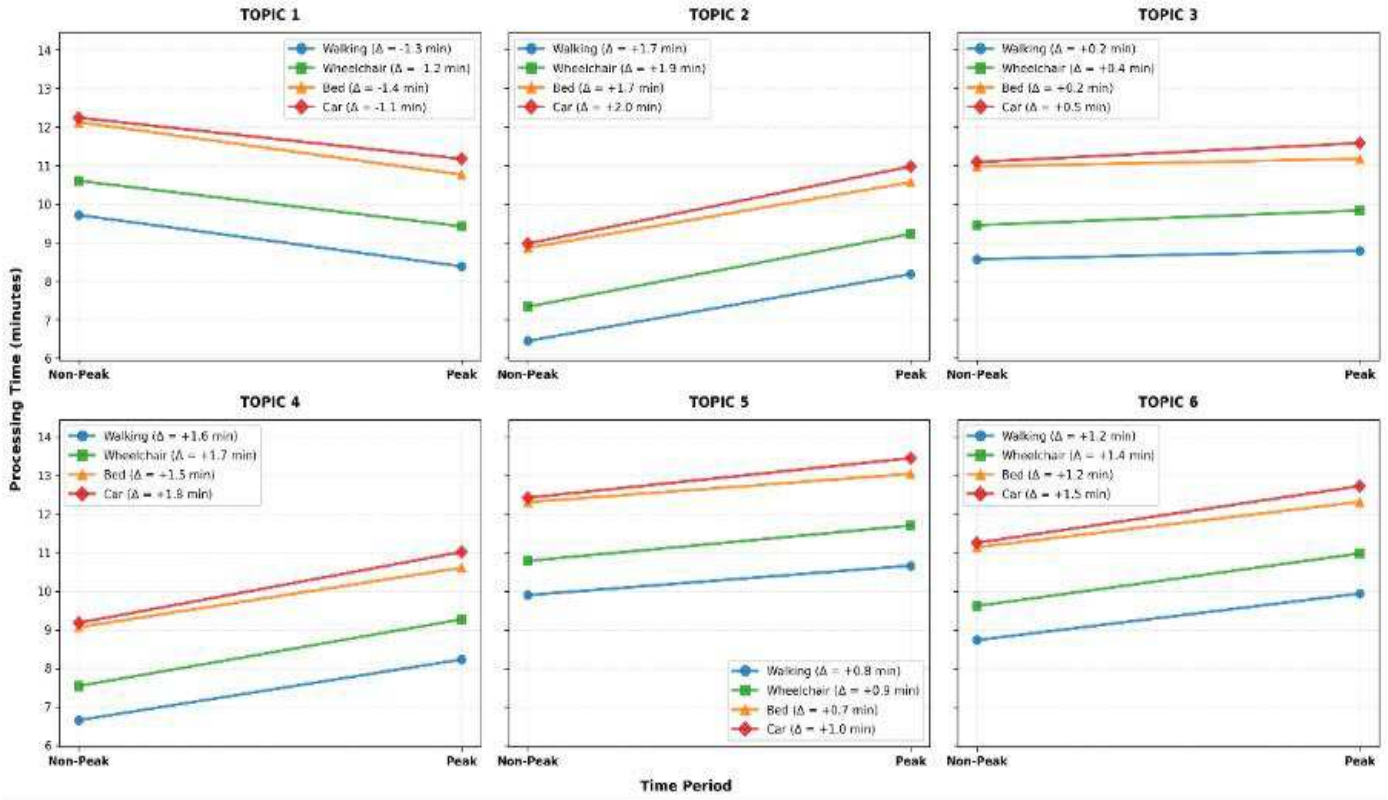


Fig. 6 Topic-specific interaction effects of peak time and transport mode on predicted transport duration.

Discussion

Principal Findings

By analyzing log data collected between 2014 and 2021 from a smartphone-based patient transport application and applying NMF-based topic classification, we identified location and time as factors influencing in-hospital patient transport, as well as the means of transport. Event-based records and transport timestamps enabled identification of workflow patterns based on temporal and spatial characteristics. This approach revealed variation in transport duration across task types, beyond the known effects of transport mode and peak times. For the most frequent transport type—transfers from inpatient wards to procedure and examination rooms (Topic 5, n = 2,384,129)—transport duration was significantly longer during peak workload times. Transport duration for other topic-defined task types also varied significantly by contextual factors. These findings demonstrate the value of routinely

collected application logs for characterizing transport workflows and identifying contexts that warrant further operational assessment.

Interpretation of Transport Characteristics by Contextual Workflow Patterns

Departure and arrival locations, transfer start times, and request times were identified as key factors in topic derivation via NMF analysis. In Topic 1, the leading contributors were the request time for non-routine tasks (45.79%) and execution time for early morning tasks (44.99%), suggesting cases where ICU transfers are pre-scheduled during dawn hours. ER (42.2%) and ICU (46.6%) were the most frequent departure and arrival locations, respectively, reinforcing this interpretation.

Topic 2 was dominated by transfers from PROC (49.11%) to WD (46.38%), likely representing post-test patient returns. Topic 3 was characterized by afternoon task request (43.58%) and execution times (44.23%), representing transfers both requested and performed within the same afternoon period. Topic 4 exhibited high proportions of morning request (47.81%) and execution times (42.30%), suggesting immediate same-morning transfers. Transfers in Topics 3 and 4 predominantly originated from PROC (70.7% and 76.5%, respectively) and ended in WD (61.5% and 67.0%, respectively). The distinction from Topic 2 likely reflects the difference between immediate same-shift transfers and advance-scheduled returns.

Topic 5 was defined by transfers from WD (48.07%) to PROC (49.49%), representing typical inpatient diagnostic transport. Topic 6 was associated with non-routine request times (44.63%) and afternoon task times (45.35%), suggesting cases with variable delays between request and transfer initiation. From a departure-location perspective, Topic 6 accounted for 33.3% of ICU-originating transports (3,993/11,992) and 54.1% of OR-originating transports (11,627/21,508).

Based on the findings, Topics 2 and 5 represent homogeneous transport flows between WD and PROC, whereas Topics 3 and 4 display greater heterogeneity, likely influenced by variability in departure planning. As shown in the violin plot of transfer request-to-start intervals (Fig 4), these topics likely reflect transfers requiring immediate execution.

In contrast, Topics 1 and 6 appear to capture more variable scenarios, including transfers involving the ER, OR, and ICU. Topic 1—despite having the fewest cases—was characterized by a high proportion of ER to the ICU related transports.

For Topic 5, which typifies inpatient transfers to PROC, morning transports (72.2%) exceeded the overall average (51.6%), whereas peak time transports (54.8%) remained below the overall average (58.0%). Given that morning peak times are defined as 09:00–11:59, these findings suggest a concentration of diagnostic transfers in the early morning. This aligns with prior findings that clinical information gathering is often concentrated around morning rounds.

Moreover, these results indicate that patient flow cannot be fully understood by transport volume or duration alone, as transport patterns are shaped by clinical urgency and origin–destination characteristics.

Interpretation of Regression Results

The distinctive characteristics of Topic 1 were reflected in the regression analysis of transport duration during peak times. Whereas all other topics showed increased transport durations during peak times, Topic 1 demonstrated a decreasing trend. Although Topic 1 represents only 0.02% of cases, ER to ICU related transports may require separate analysis from general workflows.

Transport durations varied significantly across topics and were influenced by peak times and transport modes. These findings are consistent with prior results, yet demonstrate more nuanced, variable-dependent effects. Although peak times and transport modes are not easily modifiable, they may still be amenable to process-level adjustments within hospital operations.

When transport resources (e.g., staffing levels) are flexibly allocated, transport or waiting delays may be mitigated. Although differences in transport duration may not substantially impact patient experience, their alignment with prior findings and capacity to reflect variable interactions support their use as indicators of internal hospital traffic.

The regression analysis confirmed that the effect of peak times on transport duration was small but consistent; transport mode, particularly CART or BED transport, had a stronger impact; and

directional and contextual differences between task types (e.g., WD → PROC vs. PROC → WD) produced greater time disparities—often exceeding 3 min.

In other words, peak workload times alone do not fully explain delays; when considered alongside transport context (topic) and transport mode, transport duration may serve as a sensitive indicator of hospital traffic and congestion. Topic 5 (WD → PROC) exhibited the longest transport durations, reinforcing the congestion hypothesis when combined with the observed morning-time clustering of diagnostic transfers.

This suggests that if clinical decision-making is structured around information availability for ward rounds (e.g., early test results), transfers from WD to PROC may become temporally concentrated. Moreover, a higher proportion of large transport vehicles (e.g., CART, and BED) in these flows may amplify the effects of physical bottlenecks such as elevators and corridors.

Implications for Patient Flow Management and Hospital Operations

Based on these findings, we highlight three implications for future in-hospital transport management: (1) contextual factors play a central role in analyzing patient flow and should be interpreted in conjunction with environmental variables; (2) topic-based classification enabled identification of congested scenarios, aligning with prior critiques of morning ward-round clustering and its associated inefficiencies; and (3) transfers to specialized units (e.g., ICUs and ERs) exhibit distinctive transport patterns requiring tailored operational planning. These insights may inform targeted strategies for improving transport efficiency and guiding clinical implementation efforts.

Furthermore, these findings suggest several operational strategies:

(1) Rather than focusing solely on reducing transport duration, resource redistribution should be considered to improve efficiency [3]. This is consistent with prior reports highlighting inefficiencies and patient dissatisfaction related to morning decision-making bottlenecks [29, 30].

(2) Reducing physical load—particularly the use of bulky transport devices—can contribute to shorter transport durations.

(3) Although time differences between topics were modest, our findings support the use of transport duration—when aggregated over large datasets—as a proxy indicator of workflow burden, with potential utility for resource reallocation and patient experience enhancement [8].

Strengths and Limitations

Although patient transport is recognized as important, it has received limited attention as a research topic. The strength of this study lies in its focus on transport within the broader context of hospital workflow, rather than treating it as an isolated process. Our findings demonstrate that, even in well-resourced hospitals, transport duration is sensitive to variations in workload and clinical context. Furthermore, directionality, spatial context, and transport mode had greater explanatory power for congestion than time of day alone.

Temporal variation in staff allocation was not accounted for in the analysis. Patient experience was not assessed, and no data were available regarding clinical severity. This was a single-institution study conducted at a large tertiary referral center, which may limit generalizability. However, the findings demonstrate a generalizable analytic approach for transforming routinely collected transport application logs into workflow indicators that may be adapted to other hospital information systems. Transport infrastructure and workflows (e.g., transport request timing) may differ across institutions, and thus some patterns observed may reflect local operational characteristics.

Distance and vertical floor transitions were not explicitly included as variables. Particularly, movement between floors is considered an important variable because it is highly likely to be a major bottleneck in patient transport [4, 32]. However, facility design guidelines typically recommend proximity between key departments—such as emergency and outpatient clinics and diagnostic areas, or ICU and operating rooms—within the same or adjacent floors [31]. The study hospital adhered to such standards, with core units (emergency, outpatient, ICU, and OR) positioned adjacently, suggesting limited variability in physical layout among large institutions.

Although physical factors such as transport mode significantly influenced delays, opportunities for modification may be limited.

Conclusions

Analysis of patient transport application logs revealed variation in transport duration aligned with underlying clinical workflows. Classification of transport tasks using contextual variables demonstrated that transport duration reflects operational differences across workflow contexts. These findings support the use of transport duration as a performance and planning indicator. Future studies should integrate patient-level clinical data and cross-institutional comparisons to validate generalizability and support implementation in patient flow management.

List of abbreviations

BED: bed

CART: cart

CI: confidence interval

ER: emergency room

ICU: intensive care unit

NMF: non-negative matrix factorization

OPD: outpatient department

OR: operating room

OTL: other locations

PROC: procedure and examination room

TPS: transactions per second

WC: wheelchair

WD: ward

WLK: walking

Declarations

Ethics approval and consent to participate

This study was approved by the Institutional Review Board (IRB) of Asan Medical Center, Korea (IRB 2021-0926) and conducted in accordance with relevant ethical guidelines. As this study used retrospective, de-identified application log and hospital data, the requirement for informed consent was waived by the IRB in accordance with the Bioethics and Safety Act of the Republic of Korea.

Consent for publication

Not applicable.

Availability of data and materials

The data that support the findings of this study are not publicly available because they contain institutional operational log data and access is subject to institutional review and approval. Data may be made available from the Asan Medical Center Institutional Data Access/Ethics Committee for researchers who meet the criteria for access to confidential data. Requests may be directed to irb@amc.seoul.kr or +82-2-3010-7166.

Competing interests

The authors declare that they have no competing interests.

Funding

This research was supported by a grant from the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (Grant No. RS-2025-00519560), Republic of Korea.

Authors' contributions

SK, JK, YEP, and YL contributed to the conceptualization, data curation, formal analysis, methodology, investigation, project administration, resources, supervision, validation, visualization, funding acquisition, and drafting of the manuscript according to their respective roles. SK, JK, YEP, and YL wrote the main manuscript text, and SK and JK prepared the visualizations. JK and YL

contributed to conceptualization and methodology. YL acquired funding, administered the project, provided resources, and supervised the study. JHL contributed to validation. All authors reviewed and edited the manuscript, read and approved the final manuscript.

Acknowledgements

Not applicable.

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