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# Network Analysis Examining Intrahospital Traffic of Patients With Traumatic Hip Fracture

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**ABSTRACT**

**Introduction:** Increased intrahospital traffic (IHT) is associated with adverse events and infections in hospitalized patients. Network science has been used to study patient flow in hospitals but not specifically for patients with traumatic injuries.

**Methods:** This retrospective analysis included 103 patients with traumatic hip fractures admitted to a level I trauma center between April 2021 and September 2021. Associations with IHTs (moves within the hospital) were analyzed using R (4.1.2) as a weighted directed graph.

**Results:** The median (interquartile range) number of moves was 8 (7–9). The network consisted of 16 distinct units and showed mild disassortativity (−0.35), similar to other IHT networks. The floor and intensive care unit (ICU) were central units in the flow of patients, with the highest degree and betweenness. Patients spent a median of 20–28 hours in the ICU, intermediate care unit, or floor. The number of moves per patient was mildly correlated with hospital length of stay ($\rho = 0.26$, $p = .008$). Intrahospital traffic volume was higher on weekdays and during daytime hours. Intrahospital traffic volume was highest in patients aged <65 years ($p = .04$), but there was no difference in IHT volume by dependent status, complications, or readmissions.

**Conclusions:** Network science is a useful tool for trauma patients to plan IHT, flow, and staffing.

**Keywords:** network science, intrahospital traffic, intrahospital transfer, hip fracture

## Introduction

Intrahospital traffic (IHT), the transfer or movement of patients between units, has been linked to adverse events and infections in hospitalized patients. Studies have found a number of adverse events arising with patient movement: Clostridium difficile infection (CDI), wound infections, ventilator-associated pneumonia, falls, pressure injuries, medication errors, delirium, endotracheal tube displacement, intravenous catheter displacement, cardiac arrest, metabolic events, cardiac dysrhythmias, hypotension, and hypertension.[1–5] These studies reported that greater IHT increased hospital length of stay (LOS) and intensive care unit (ICU) LOS, and mortality in critically ill patients.[1,5]

Hip fractures present a particularly interesting subset of injuries because they occur in older populations with concurrent comorbidities who need to be transferred into surgery as quickly as possible.[6–8] Timing and flow of IHT in patients with hip fractures is important, because faster performance of perioperative procedures (radiology, blood tests, etc.) and surgical procedures lead to lower mortality, improved autonomy, and fewer pressure ulcers.[7,9,10] There is scant literature on IHT in the hip fracture population, although Bristol and colleagues identified specific complications and outcomes of more IHTs in the geriatric population including delirium, hospital LOS, and mortality/morbidity.[1,11] This study investigates IHTs in patients with hip fractures to gain more insight into patient flow during their hospital stay using network science.

Network science is an ever-expanding tool used in healthcare. Network analysis has been used to model disease outbreaks,[12,13] describe physician referral networks,[14] follow pathogen spread between hospitals,[15] and illustrate patient flow from admission to discharge.[16–18] Networks consist of nodes and edges, where a node represents a unique location or person, and an edge represents the connection between two nodes, such as a movement of a patient from one hospital location to another. Network analysis has

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also been used to study IHTs to identify hubs (locations very important to patient flow) and bottlenecks (locations with higher patient flow in than out) and temporal differences in patient flow to improve future patient care.[16–18] The aim of this study is to describe patient flow at a Level I trauma center specifically for patients with hip fractures and determine any temporal differences or contrasts in outcomes.

## Methods

This retrospective analysis included patients with a traumatic hip fracture who were admitted to a Level I trauma center in Colorado from April through September 2021. Hip fractures were identified by the International Classification of Diseases 10th Revision diagnosis codes S72.00-S72.14. Patients were excluded if they left against medical advice (n = 0), were transferred from another hospital (n = 17), or were aged less than 18 years (n = 0). This study was institutional review board–approved (ID: 1829515).

The hospital's trauma registry was queried for patient information including age, sex, admission vital signs (heart rate, respiratory rate, and systolic blood pressure), cause of injury, Glasgow Coma Scale (scores of 3–8 signify severe neurologic injury), injury severity score (ISS; scores ≥16 signify severe traumatic injury), discharge disposition, LOS, comorbidities, and complications. These variables were abstracted from the electronic health record (EHR) into the trauma registry by dedicated trauma registrars using the State department of public health data dictionary.

Intrahospital traffic (location, date, and time) was abstracted from the EHRs by a dedicated clinical research coordinator. The EHR provides all patient activity in a linear continuum from arrival to discharge. Activity includes not only intrahospital transfers, but also orders, medications, etc. Intrahospital transfers were identified by manually reviewing patient activity. Room changes within the same location were also documented in the EHR. Intrahospital traffic locations included the emergency department (ED), radiology department (for computed tomography [CT], X-ray, and ultrasound), preoperative (Pre-Op) holding, operating room (OR), postanesthesia care unit (PACU), floor (medical/surgical bed), ICU, immediate care unit (IMCU), and discharge locations (home, home health, hospice, morgue, inpatient rehab, and skilled nursing facility [SNF] or nursing home).

Antibiotic use before injury and during hospitalization, and result of CDI culture (if performed) were also abstracted from the EHR.

Network metrics calculated include volume (number of moves between units) order (number of nodes), size (number of edges), degree (number of edges connected to node), in-degree and out-degree (patient flow in and out of a location), strength (degree weighted by the number of moves), betweenness (location dependencies), density (number of edges divided by possible number of edges), assortativity (similarity of neighboring nodes), and reciprocity (measure of the proportion of mutual connections). A unit was considered a hub when the degree was larger than the average degree.[19]

Intrahospital traffic volume was also examined in four subcohorts defined a priori: (1) age categories, (2) dependent comorbidity (considered a marker of frailty besides age), (3) development of a complication, and (4) 30-day readmission. In addition, subnetworks of night-time transfers (6:00 p.m.–6:00 a.m.) and weekend transfers (Saturday and Sunday) were compared with daytime transfers and weekday transfers.

### *Statistical Analysis*

All data analyses were performed in R (**r-project.org**, version 4.1.2). Patient demographics, injury characteristics, and transfer patterns were summarized by frequency and percent or median and interquartile range (IQR). Intrahospital traffic volume were analyzed with Wilcoxon rank-sum tests (2 group comparison) or Kruskal–Wallis tests (multigroup comparison). The correlation between IHT volume and LOS was analyzed with Spearman rank correlation.

The network was analyzed in R as a weighted directed graph using the "igraph" package (**igraph.org/r**).[20] For this study, the nodes are the hospital units, and an edge is a move between units (IHTs). Transfers from one bed to another within the same unit were also analyzed.

## Results

There were 103 patients included. Table 1 presents the demographics and outcomes of these patients. The majority of patients were aged older than 75 years and female. Falls were the most common cause of hip fractures (94%). The average hospital LOS was 5 days, and the average ISS was 9. None of the patients had a CDI culture performed. Most (59%) patients were discharged to a SNF.

**Table 1. Demographics and Clinical Characteristics of Hip Fracture Patients**

| Characteristics | No. of observations | Frequency | Characteristics | n obs | Frequency |
|---|---|---|---|---|---|
| Age, years | 103 | | GCS 13–15 | 101 | 101 (100%) |
| <65 | | 10 (9.7%) | Heart rate <60 or >120 bpm | 96 | 7 (7.3%) |
| 65–74 | | 23 (22.3%) | SBP < 90 mm Hg | 96 | 2 (2.1%) |
| 75–84 | | 26 (25.2%) | Respiratory rate <12 or >20 b/m | 92 | 7 (7.6%) |
| 85+ | | 44 (42.7%) | Medications prehospital | 103 | |
| Female | 103 | 64 (62.1%) | Anticoagulant use | | 13 (12.6%) |
| Cause of injury | 103 | | Smoker | | 17 (16.5%) |
| Fall | | 97 (94.2%) | Steroid use | | 1 (1%) |
| Transport or GSW | | 6 (5.8%) | Chemotherapy | | 1 (1%) |
| Median ISS | 103 | 9 (9–9) | Antibiotics | | 1 (1%) |
| Comorbidities | 103 | | Median hospital LOS (days) | 102 | 5 (4–6) |
| Advanced directive | | 27 (26.2%) | Median ICU LOS (days) | 10 | 3 (2–3.75) |
| Dependent health | | 55 (53.4%) | Discharge disposition | 103 | |
| Chronic heart failure | | 12 (11.7%) | Expired/morgue | | 3 (2.9%) |
| COPD | | 22 (21.4%) | Home | | 13 (12.6%) |
| Dementia | | 20 (19.4%) | Home health | | 7 (6.8%) |
| Diabetes mellitus | | 18 (17.5%) | Hospice | | 3 (2.9%) |
| Hypertension | | 59 (57.3%) | Inpatient rehab | | 15 (14.6%) |
| CDI culture performed | 103 | 0 (0%) | SNF | | 62 (60.2%) |

Data are presented as median (IQR) or n (%).
One patient was discharged to a nursing home and was combined with SNF discharge disposition.
CDI = clostridium difficile infection; COPD = chronic obstructive pulmonary disease; b/m = breaths per minute; bpm = beats per minute; GCS = Glasgow Coma Scale; GSW = gunshot wound; ICU = intensive care unit; IQR = interquartile range; ISS = injury severity score; LOS = length of stay; SBP = systolic blood pressure; SNF = skilled nursing facility.

The IHT network consisted of 16 units (order) and 56 unique moves (size; Figure 1). The network showed a low density of 0.23 and an assortativity of −0.35, making it disassortative. The degree of each unit ranged from 1 to 23, indicating some units were highly connected and others were not. The median degree was 7, making the hubs of this network the floor, ICU, radiology department, and the OR. The ED and floor had a negative difference in in-degree and out-degree, meaning that there was more traffic in than out of these two units. The floor was, not surprisingly, the strongest unit, where strength is a measure of the traffic going in and out of that unit, essentially a weighted degree. Unit degree and betweenness were well correlated ($\rho = 0.80$, $p < .001$). The floor and the ICU were central units to the flow of patients having the highest degree and betweenness.

Intrahospital traffic volume is shown in Figure 2. The majority of IHT occurred in and out of the floor and the ED. The median IHT volume per patient was 8 (IQR: 7–9). Patients spent a median of 20–28 hours in the ICU, IMCU, or the floor (Figure 3A). Most patients spent less than 2 hours in radiology, Pre-Op holding, OR, and PACU (Figure 3B). IHT volume was mildly correlated with hospital LOS ($\rho = 0.26$, $p = .008$).

Intrahospital traffic volume by subcohorts of interest are shown in Table 2. Intrahospital traffic volume differed by age groups, with patients aged

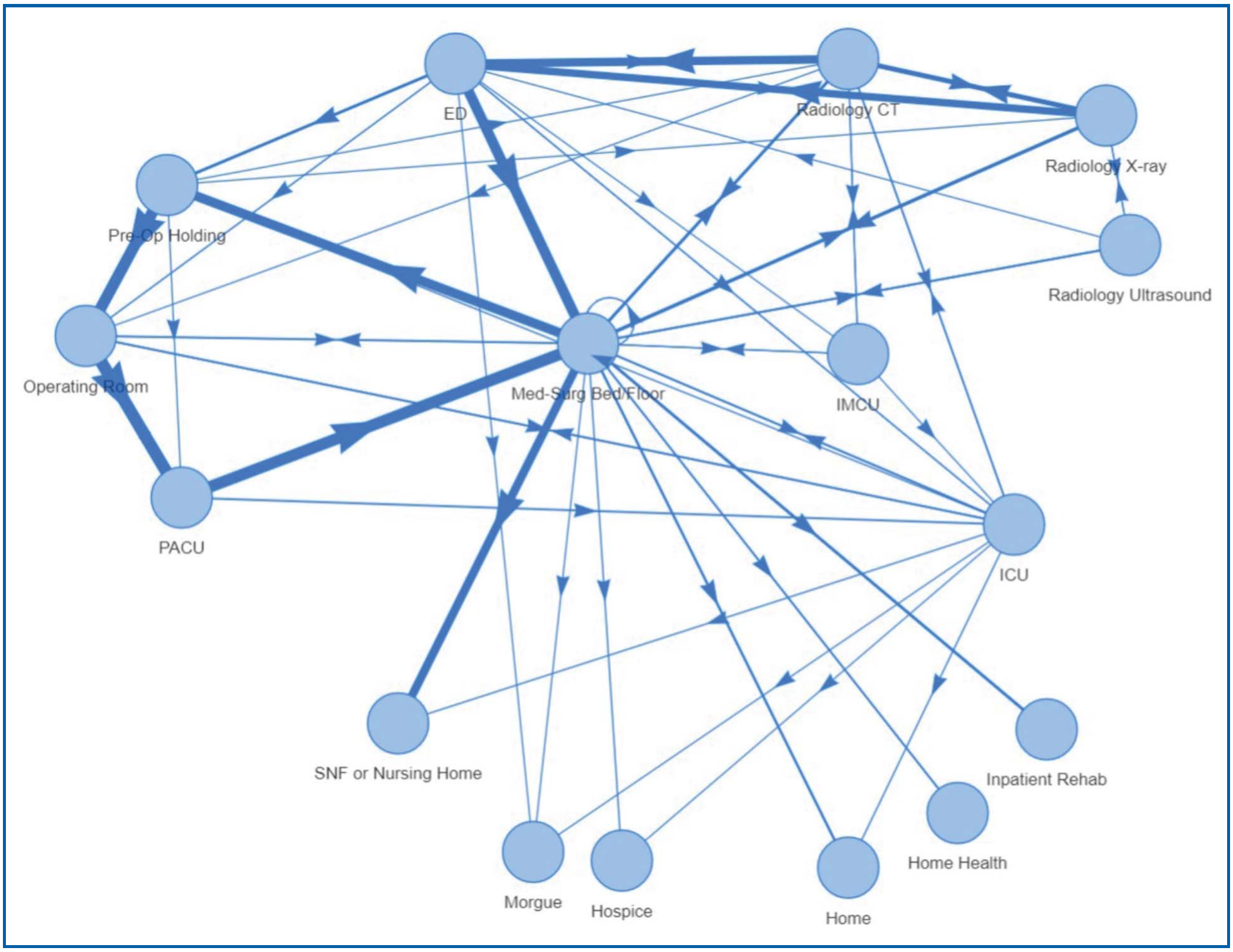


**Figure 1.** The network of intrahospital transfers for hip fracture patients. The thickness of the lines denotes the weighted degree of a transfer. There is clear directional flow from Pre-Op holding to the OR to PACU. Radiology has a strong connection to the ED. The floor is central to many of the units, including the ED and the Pre-Op holding unit, OR, and PACU units. Many of the patients were transferred to a SNF or nursing home at discharge. CT = computed tomography; ED = emergency department; OR = operating room; PACU = postanesthesia care unit; Pre-Op = preoperative; SNF = skilled nursing facility.

≤65 years (n = 10) having higher IHT volume of one or more moves between units than the other age groups ($p = .04$). Seven patients had a complication including cardiac arrest, delirium, pressure ulcer, or unplanned return to the ICU or OR. Patients with complications did not show a significant increase in IHT volume. Similarly, there was no difference in IHTs by dependent status or readmission status. There were not enough patients with complications, with 30-day readmission, or within age categories to examine additional network metrics, besides IHT volume, among these subcohorts. Patients claimed as dependents compared with patients not claimed as dependents had a similar network in terms of order (16 vs. 15) and size (43 vs. 45), but dependent patients had slightly lower density network (0.18 vs. 0.21) and slightly lower reciprocity (0.47 vs. 0.50).

Comparing temporal subsets, patient flow was higher on weekdays versus the weekends based on network size (52 vs. 35) and density (0.22 vs. 0.17). Daytime transfers were more common than nighttime transfers based on network size (49 vs. 35), density (0.20 vs. 0.19), and reciprocity (0.50 vs. 0.47).

### Limitations

The primary limitation is that this was a pilot study designed in part to determine the feasibility of evaluating IHT for patients with traumatic injuries.

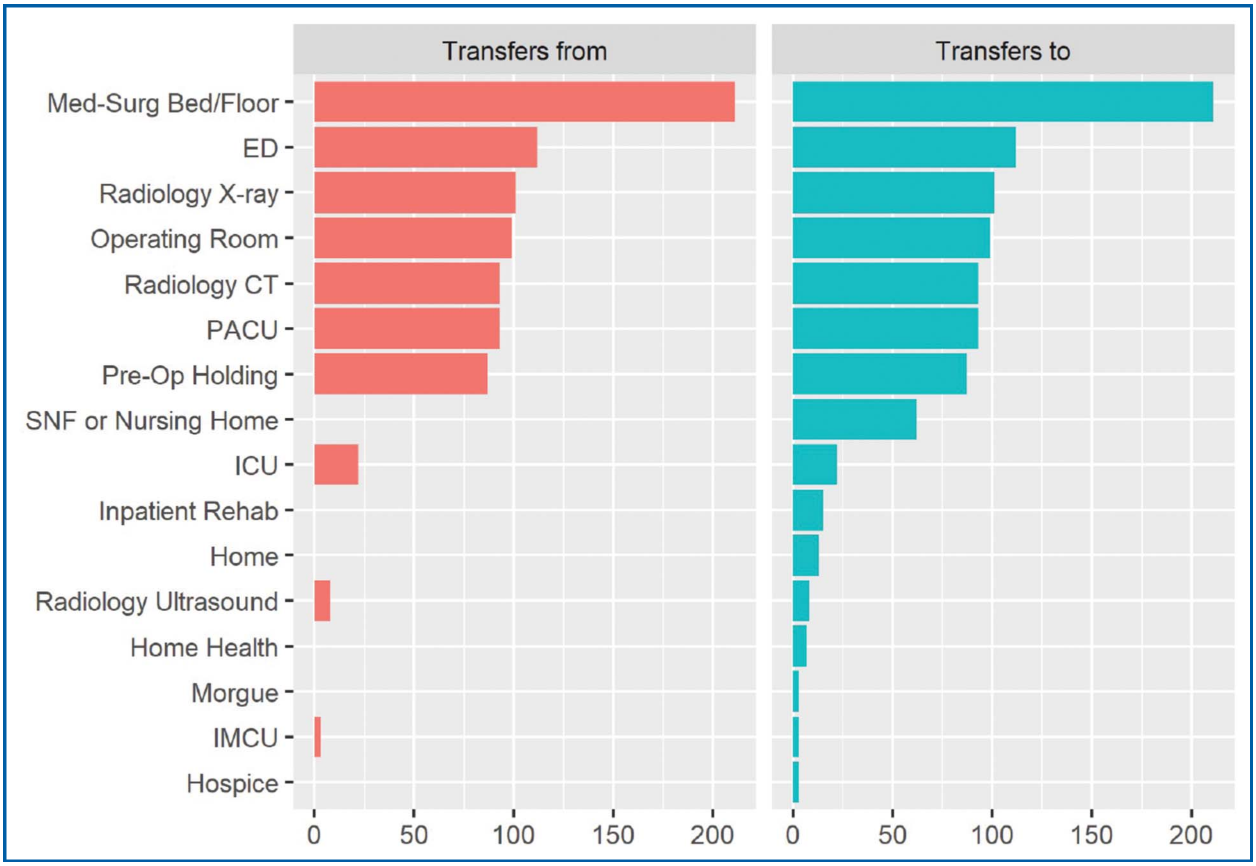


**Figure 2.** Number of transfers from and to each unit. CT = computed tomography; ED = emergency department; ICU = intensive care unit, IMCU = immediate care unit; PACU = postanesthesia care unit; SNF = skilled nursing facility.

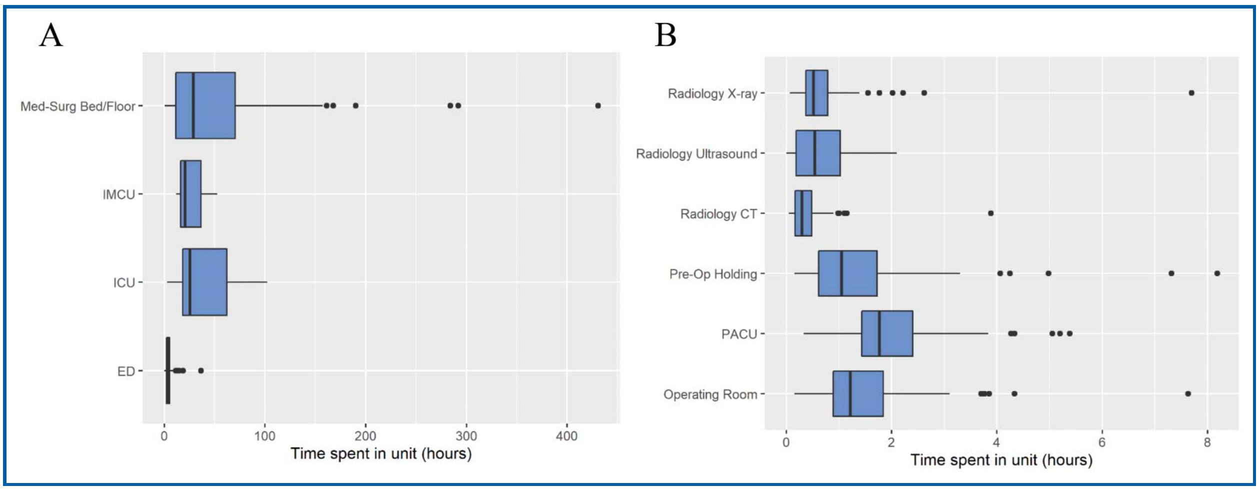


**Figure 3.** Time spent in each unit. A, The floor, ICU, IMCU, and ED. B, Time spent in radiology and OR. CT = computed tomography; ED = emergency department; ICU = intensive care unit, IMCU = immediate care unit; OR = operating room.

**Table 2. Association Between IHT Volume and Demographic and Clinical Characteristics**

| Covariate | N | IHT volume | *p* value |
|---|---|---|---|
| Overall | 103 | 8 (7–9) | — |
| Age <65 years | 10 | 9 (8–10) | .04 |
| Age 65–74 years | 23 | 7 (7–8) | |
| Age 75–84 years | 26 | 8 (6–9) | |
| Age ≥ 85 years | 44 | 8 (7–9) | |
| Dependent | 55 | 8 (7–9) | .28 |
| Independent | 48 | 8 (6.5–9) | |
| Complication | 7 | 9 (7–11) | .34 |
| No complication | 96 | 8 (7–9) | |
| Readmission within 30 days | 7 | 8 (8–9.5) | .26 |
| Not readmitted | 96 | 8 (7–9) | |

Associations with volume (number of moves between units) were analyzed with Wilcoxon rank-sum tests for dependent status (yes/no), complication (yes/no), and readmission (yes/no), and Kruskal–Wallis test for age categories. Bold number denotes statistical significance $p<0.05$.
IHT = intrahospital traffic.

We demonstrated that this type of study is feasible in a U.S. hospital setting. Second, the pilot study utilized a convenience sample of patients admitted over a six-months period; we limited this date range because of the labor-intensive nature of chart abstraction, which included IHT with dates and times for each patient. Third, because the study was limited to a 6-month period, there may be seasonal differences in patient movement that were not captured. Fourth, transfers during a SARS-CoV-2 outbreak may not be comparable with transfers made during regular times. Finally, complications specifically due to an IHT are usually not recorded in a patient's chart. The progress notes and discharge notes were reviewed for complications attributable to an IHT, but we were limited to what was documented and some complications may be missing.

## Discussion

Network science is a useful tool for visualizing patient flow through the hospital, identifying central units, and comparing differences in flow between subcohorts. It has not been previously used to study trauma patients exclusively, and most of the literature reporting on IHTs using network science are in the United Kingdom or Europe.

The IHT network for patients with hip fractures showed mild disassortativity, similar to an IHT network in a U.K. hospital.[17] Assortativity is often operationalized as correlation between nodes. In the hospital setting such as trauma admissions, large-degree units like the floor are connected to many other units, but most of them are smaller-degree units. Likewise, smaller-degree units such as radiology (x-ray, CT, and ultrasound) are not frequently connected to each other or to other small-degree units, making the network disassortative. The finding that the hip fracture IHT network showed mild disassortativity was not unexpected because biological networks tend to be less assortative compared with social networks that are more assortative. Potential areas for further study include examining structural similarities between this network of patients with hip fracture to networks of patients with other injuries or indications, or comparing hip fracture populations across facilities with different underlying demographics or levels of care.

This study found differences in the IHT network on weekends versus weekdays, similar to a study at two U.K. hospitals that found a weekend-weekday effect on hospital flow.[16] Two studies used network science to track and model the connection between IHTs and CDI and hospital-acquired infections.[13,18] This study did not have any patients who were tested for CDI, but this is not surprising, given the sample size.

The network for patients claimed as dependents was less dense than patients not claimed as dependents, meaning that units were not as connected for these patients, so their movement through the hospital was not as varied. One potential explanation for this reduced density is the higher percentage of advanced directives among patients claimed as dependents (42%) compared with patients who were independent (8%). An advanced directive may limit types of IHT, leading to fewer connections between departments, making the network less dense.

## Conclusions

Network science may be a useful tool for patients with traumatic injuries to examine patient volume and flow, for staffing, and to examine complications and discharge location.

## Implications

IHT networks can be used in the clinical setting by departments to plan staffing, by infectious disease specialists to examine infection prevention strategies, or to monitor commonalities in transfer-related complications. Network science is especially relevant in hospital settings where departments are highly interconnected. IHT networks could provide a more comprehensive, systemwide review of any changes made within a specific department. In addition, the research applications of network science for examining IHTs are numerous, including the aforementioned comparison of IHTs across diagnoses or across facilities to examine heterogeneity or outliers. This study is a teaser to what network science could do for monitoring patient flow, especially for patients admitted with traumatic injuries in a U.S. hospital.

## Authors' Biographies

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**David Bar-Or, MD,** is the Director of ION Research in Englewood, CO. He oversees all studies conducted by ION research and is involved with every aspect of the ION Research team studies from study hypothesis generation, protocol development, to drafting and reviewing articles. He is also an adjunct professor at Kansas City University in Kansas City, MO, and Rocky Vista University in Parker, CO.

## References

1. Bristol AA, Schneider CE, Lin SY, Brody AA. A systematic review of clinical outcomes associated with intrahospital transitions. *J Healthc Qual*. 2020;42(4):175-187.
2. Durak VA, Armagan E, Ozdemir F, Kahriman N. Discharge of emergency patients to the clinical wards or intensive care units: An assessment of complications and possible shortcomings. *Injury*. 2015;46(suppl 2):S53-S55.
3. Knight PH, Maheshwari N, Hussain J, et al. Complications during intrahospital transport of critically ill patients: Focus on risk identification and prevention. *Int J Crit Illn Inj Sci*. 2015;5(4): 256-264.
4. Parveez MQ, Yaddanapudi LN, Saini V, Kajal K, Sharma A. Critical events during intra-hospital transport of critically ill patients to and from intensive care unit. *Turk J Emerg Med*. 2020;20(3):135-141.
5. Schwebel C, Clec'h C, Magne S, et al. Safety of intrahospital transport in ventilated critically ill patients: A multicenter cohort study*. *Crit Care Med*. 2013;41(8):1919-1928.
6. Guo Z, Zhao F, Wang Y, Wang X. Intensive care unit resource utilization after hip fracture surgery in elderly patients: Risk factor identification and risk stratification. *Orthopedics*. 2020; 43(3):E159-E165.
7. Grant-Freemantle MC, Kenyon RM, Gibbons J, Flynn SO, Davey M, Burke N. Assessing the time to ward transfer in patients presenting to the emergency department with an acute hip fracture: A closed-loop audit. *Cureus*. 2020;12(1): e6794.
8. Griffiths R, Babu S, Dixon P, et al. Guideline for the management of hip fractures 2020: Guideline by the Association of Anaesthetists. *Anaesthesia* 2021;76(2): 225-237.
9. Hughes AJ, Brent L, Biesma R, Kenny PJ, Hurson CJ. The effect of indirect admission via hospital transfer on hip fracture patients in Ireland. *Ir J Med Sci*. 2019;188(2):517-524.
10. Gomez M, Rony L, Marc C, et al. Fast-track care for pertrochanteric hip fracture: What impact on function and autonomy after discharge? *Orthop Traumatol Surg Res*. 2020; 106(4):633-637.
11. Bristol AA. Geriatric nurse involvement during intra-hospital transitions. *Geriatr Nurs*. 2019;40(5):543-545.
12. Eubank S, Guclu H, Kumar VSA, et al. Modelling disease outbreaks in realistic urban social networks. *Nature*. 2004; 429(6988):180-184.
13. McHaney-Lindstrom M, Hebert C, Miller H, Moffatt-Bruce S, Root E. Network analysis of intra-hospital transfers and hospital onset clostridium difficile infection. *Health Info Libr J*. 2020;37(1):26-34.
14. An C, O'Malley AJ, Rockmore DN, Stock CD. Analysis of the U.S. patient referral network. *Stat Med*. 2018;37(5): 847-866.
15. Piotrowska MJ, Sakowski K, Karch A, et al. Modelling pathogen spread in a healthcare network: Indirect patient movements. *PLoS Comput Biol*. 2020;16(11):e1008442.
16. Bean DM, Stringer C, Beeknoo N, Teo J, Dobson RJB. Network analysis of patient flow in two UK acute care hospitals

identifies key sub-networks for A&E performance. *PLoS One*. 2017;12(10):e0185912.
17. Kohler K, Ercole A. Can network science reveal structure in a complex healthcare system? A network analysis using data from emergency surgical services. *BMJ Open*. 2020;10(2):e034265.
18. Tahir H, Lopez-Cortes LE, Kola A, et al. Relevance of intra-hospital patient movements for the spread of healthcareassociated infections within hospitals - a mathematical modeling study. *PLoS Comput Biol*. 2021; 17(2):1-23.
19. Barrat A, Barthélemy M, Pastor-Satorras R, Vespignani A. The architecture of complex weighted networks. *Proc Natl Acad Sci U S A*. 2004;101(11):3747-3752.
20. Gábor C, Tamás N, Edoardo MA. *Statistical Network Analysis With Igraph*. 2016. https://sites.fas.harvard.edu/~airoldi/pub/books/BookDraft-CsardiNepuszAiroldi2016.pdf.