BMJ Open

Effects of patient-level risk factors, departmental allocation and seasonality on intrahospital patient transfer patterns: network analysis applied on a Norwegian single-centre data set

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To cite: Zhang C, Eken T, Jørgensen SB, *et al*. Effects of patient-level risk factors, departmental allocation and seasonality on intrahospital patient transfer patterns: network analysis applied on a Norwegian single-centre data set. *BMJ Open* 2022;**12**:e054545. doi:10.1136/bmjopen-2021-054545

► Prepublication history and additional supplemental material for this paper are available online. To view these files, please visit the journal online (http://dx.doi.org/10.1136/bmjopen-2021-054545).

Received 16 June 2021
Accepted 01 March 2022

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ABSTRACT

Objectives Describe patient transfer patterns within a large Norwegian hospital. Identify risk factors associated with a high number of transfers. Develop methods to monitor intrahospital patient flows to support capacity management and infection control.

Design Retrospective observational study of linked clinical data from electronic health records.

Setting Tertiary care university hospital in the Greater Oslo Region, Norway.

Participants All adult (≥18 years old) admissions to the gastroenterology, gastrointestinal surgery, neurology and orthopaedics departments at Akershus University Hospital, June 2018 to May 2019.

Methods Network analysis and graph theory. Poisson regression analysis.

Outcome measures Primary outcome was network characteristics at the departmental level. We describe location-to-location transfers using unweighted, undirected networks for a full-year study period. Weekly networks reveal changes in network size, density and key categories of transfers over time. Secondary outcome was transfer trajectories at the individual patient level. We describe the distribution of transfer trajectories in the cohort and associate number of transfers with patient clinical characteristics.

Results The cohort comprised 17 198 hospital stays. Network analysis demonstrated marked heterogeneity across departments and throughout the year. The orthopaedics department had the largest transfer network size and density and greatest temporal variation. More transfers occurred during weekdays than weekends. Summer holiday affected transfers of different types (Emergency department-Any location/Bed ward-Bed ward/To-From Technical wards) differently. Over 75% of transferred patients followed one of 20 common intrahospital trajectories, involving one to three transfers. Higher number of intrahospital transfers was associated with emergency admission (transfer rate ratio (RR)=1.827), non-prophylactic antibiotics (RR=1.108), surgical procedure (RR=2.939) and stay in intensive care unit or high-dependency unit (RR=2.098). Additionally, gastrosurgical (RR=1.211), orthopaedic (RR=1.295) and neurological (RR=1.114) patients had higher risk of many transfers than gastroenterology patients (all effects: p<0.001).

Conclusions Network and transfer chain analysis applied on patient location data revealed logistic and clinical associations highly relevant for hospital capacity management and infection control.

Strengths and limitations of this study

- ► Strengths of this study include its comprehensive data set with time-stamped patient-level information on intrahospital transfers, admission type, demographics, physiological derangement and antibiotic use.
- ► Both static and temporal network analysis methods were applied to capture different aspects of patient flow.
- ► Regression techniques complemented the network analyses, assessing associations between patient-level risk factors and longer intrahospital transfer trajectories.
- ► Limitations of the study include a 12-month data set, hampering robust analysis of yearly seasonality.
- ► Data were limited to patients in four hospital departments, precluding network analysis at an all-hospital or interhospital level.

INTRODUCTION

Hospitals are complex systems which must run smoothly to ensure treatment quality and patient safety. Transfer of patients between specialised departments is a key part of hospital operation, and optimisation of patient flows is crucial for hospital capacity management and infection control.

Patients' journeys through the hospital may be analysed from different viewpoints. At a *systemic* level, assessment of overall transfer patterns makes it possible to identify logistic problems and make adequate adjustments.

Improved bed utilisation to counter unanticipated undercapacity and overcapacity in different hospital wards may reduce variability of workload and stress for hospital personnel. However, placement of patients in inappropriate settings may reduce quality of care and increase the risk of errors.[1] Physically moving patients also carries a risk of introducing infectious agents to new staff and hospital areas. Certain locations and the transfers between them may be crucial for hospital operation, and some pathways may be especially vulnerable to, for example, understaffing or closure during an infection outbreak.[2] At an *individual* level, each transfer requires handover of medical information, its quality and completeness being essential for error avoidance and continuity of care. Hospitalised patients who are frequently transferred have increased risk of falls, delirium, prolonged hospital length of stay (LOS), healthcare-associated infections and mortality.[3–6] Characterisation of transfer patterns both at a systemic and an individual level may thus be relevant for understanding and revising healthcare service use. For organisational planning, smoothed, long-term transfer data showing major patient flows and seasonality are key. In contrast, real-time data reveal the extremes and allow for immediate intervention, for example, when monitoring detects excessive staff workload or single patients subjected to transfer pathways known to carry unacceptable risk.

Intrahospital patient transfers have been studied using graph theory and network analysis. Construction of a weighted, directed transfer network describing the emergency surgical services in a UK hospital identified potential hubs and bottlenecks in the system.[2] Static and temporal transfer networks of patient flow in two UK acute care hospitals were evaluated and related to emergency department (ED) performance.[7] Interdepartmental patient transfer networks for five European hospitals were constructed and used in a simulation study of infection spread among high-risk and low-risk patient groups.[8] Network analysis has also been applied on national,[9] regional[10] and simulated[11] patient transfer data to elucidate spread of resistant microbes.

The above studies almost exclusively evaluated transfer networks for entire hospital systems. Most studies analysed networks as static entities, without attention to possible temporal changes in size or connectivity. Furthermore, network analysis alone is insufficient to describe individual patient trajectories, since in this method each patient's intrahospital journey is broken up into a number of separate location-to-location moves. All transfers are then analysed collectively without regard to their sequence.

In this study, we examined patient transfers in a large Norwegian hospital using electronic health record data. Our primary objective was to describe intrahospital transfer patterns at a systemic level. To this end, we applied network analysis on all transfers in four hospital departments, highlighting the heterogeneity of transfer patterns across departments and over time. Our secondary objective was to evaluate transfers on an individual level. We identified typical and atypical transfer trajectories and assessed whether patient characteristics, including admission type, age, gender, surgery, antibiotic use and physiological derangement, were associated with a higher number of intrahospital transfers.

METHODS

Hospital characteristics

This retrospective, observational cohort study analysed data from Akershus University Hospital (AUH), Norway, a tertiary hospital serving a population of 560 000 within the Greater Oslo Region. Patients who need cardiac surgery and neurosurgery or suffer from major trauma are referred elsewhere. In 2019, AUH had 763 somatic (non-psychiatric) beds, 66 280 somatic admissions, 33 886 day cases and 366 858 somatic ambulatory consultations. The ED is an integrated division of the hospital and predominantly receives urgent cases arriving by ambulance and prescreened patients from local emergency medical centres. Approximately 75% of patients presenting in the ED are transferred to other hospital wards. Two surgical suites together provided 22 operating rooms (ORs). Two mixed medical-surgical intensive care units (ICUs), one cardiac high-dependency unit (HDU) and one mixed postoperative care unit/HDU together provided 14 invasive and eight non-invasive ventilator beds.

Data collection

Pseudonymised data were extracted on 6 December 2019 by the AUH Department for Data Extraction and Analysis and stored and processed within the Service for Sensitive Data at the University of Oslo. The study period was 365 days starting at a Monday in June 2018; the exact week number was not released to the authors for privacy protection reasons. For time-stamped data, the granularity of time is hourly.

All adult (≥18 years) admissions to any ward in the departments of gastroenterology, gastrointestinal surgery, neurology or orthopaedics in the study period were included. The four departments, two medical and two surgical, each containing one to three wards (table 1, online supplemental table S1), were selected because they treat defined patient groups that were expected to differ from each other. Study sample size was not predefined. The cohort only contained admissions occurring after the study start time and hence excluded patients who were already admitted. Stays with incomplete or erroneous data (eg, missing LOS, negative time durations) were excluded. For patients with multiple hospital stays within the study period, each stay was treated as a unique event.

We extracted time-stamped patient location data throughout each stay to construct individual intrahospital transfer trajectories. The following information was also extracted from AUH electronic health records: demographics (age, gender), admission type (elective or emergency), time of hospital admission, physiological

Table 1 Clinical and location characteristics of study cohort

Department	Gastroenterology		Gastrosurgery		Neurology		Orthopaedics	
Admissions (n)	1712		5522		4788		5176	
Surgical procedure	Yes	No	Yes	No	Yes	No	Yes	No
(n, p1%)	69	1643	1942	3580	46	4742	3171	2005
	4.0	96.0	35.2	64.8	1.0	99.0	61.3	38.7
Emergency admission (n, p1%, p2%)	49	1059	1029	3043	45	3944	1643	1605
	2.9	61.9	18.6	55.1	9.3	82.4	31.7	31.0
	71.0	64.4	53.0	85.0	97.8	83.2	51.8	80.0
Antibiotic use (n, p1%, p2%)	39	337	663	1176	9	527	1272	317
	2.3	19.7	12.0	21.3	1.9	11.0	24.6	6.1
	56.5	20.5	34.1	32.8	19.6	11.1	40.1	15.8
Cohort characteristics								
Age	65	65	58	62	51	64	68	69
	36–81	30–85	28–80	31–83	35–75	32–84	40–85	35–88
NEWS2 score	4	2	3	2	1	2	3	2
	1–8	0–6	1–6	0–6	0–3	0–5	1–6	0–6
Hospital LOS (days)	5.3	2.0	3.9	2.0	2.2	2.8	4.3	1.2
	1.2–13	0.5–7.9	1.1–13	0.5–7.1	0.8–7.2	0.7–10	1.3–12	0.3–5.8
	44	86	184	90	49	113	84	43
Unique wards visited	4	2	4	2	4	2	4	2
	3–5	1–3	3–5	1–3	3–5	1–2	3–5	1–3
	6	4	7	5	6	6	9	5
Individual transfers	3	1	3	1	2	1	3	1
	1–4	0–2	2–4	0–2	2–3	0–1	2–5	0–2
	7	6	21	9	4	8	23	6

Ward	Type	n	Gastroenterology	Gastrosurgery	Neurology	Orthopaedics
Emergency department	ED	12 370	1101	4058	3980	3231
Operating room	OR	5032	67	1828	45	3092
Day surgery		235	2	119	1	113
Postoperative HDU	Technical	5444	144	2018	99	3183
General ICU		134	8	75	24	27
Medical ICU		201	86	45	47	23
Cardiac HDU		2			1	1
ED observation unit		2036	531	747	54	704
Haemodialysis		8	2			6
Orthopaedics A	Surgical	2144		11	2	2131
Orthopaedics B		1849		13		1836
Orthopaedics C		603	1	9		593
Gastrosurgery A		2328	5	2301	2	20
Gastrosurgery B		2488	4	2462	1	21
Mixed surgery		197	2	101	1	93
Urology		534	4	386	2	142
Thoraco-vascular		496		166	1	329

Continued

Table 1 Continued

Department			Gastroenterology	Gastrosurgery	Neurology	Orthopaedics
Neurology A	Medical	2521	2	1	2516	2
Neurology B		2245	5	1	2237	2
Neurological rehabilitation		306			306	
Gastroenterology		1263	1246	15		2
Palliation A		8		8		
Geriatrics		5	1	2		2
Palliation B		11				11
Infection/haema		14	8	4		2
Infection A		20	8	8	1	3
Cardiac		9		3	1	5
Cardiac/renal		8	3	3	1	1
Pulmonary A		2		1		1
Pulmonary B		1				1

Upper panel: cohort summary for four hospital departments, stratified by whether patient stay involved surgery. Antibiotic use excludes surgical antimicrobial prophylaxis. *Middle panel*: patient characteristics in each subcohort. Unique wards refer to the number of unique wards visited during each patient stay. Age and NEWS2 are reported as median and 10th–90th percentiles. LOS, unique wards visited and number of transfers are reported as median, 10th–90th percentiles and maximum. *Lower panel*: number of visits to each of 30 observed wards by patients' allocated department.

ED, emergency department; HDU, high-dependency unit; ICU, intensive care unit; LOS, length of stay; n, number of patient stays; NEWS2, National Early Warning Score 2 (maximum value in the first 48 hours); OR, operating room; p1%, percentage of all patient stays in the department; p2%, percentage of patient stays in the department with same surgery status.

derangement measured as National Early Warning Score 2 (NEWS2[12]), administration of antibiotics (excluding surgical prophylaxis) and whether the patient underwent a surgical procedure. The term 'patient record' refers to all data collected during a stay at the hospital.

Key variable definitions

At AUH, NEWS2 is routinely scored in the ED and three times daily in bed wards. The maximum and mean NEWS2 for each patient during their first 48 hours of stay were used in analyses, to use NEWS2 as a marker of physiologically deranged state around hospital admission. Any non-prophylactic antibiotic use during a stay was coded as a binary *yes-no* variable. Hospital LOS was converted to days. ICUs, HDUs and ORs were collectively denoted *Technical* wards. A surgical procedure was assumed for stays with OR or day surgery unit in the location log. In line with Norwegian hospital routine, the transition from one hospital day to the next was defined to occur at 07:00 hours. Weekdays and weekends were Monday to Friday and Saturday to Sunday, respectively.

Intrahospital transfer, or transfer for brevity, is a patient movement from one physical location (ward, ED, etc) to another. For perioperative transfers, we chose to combine multiple *consecutive* patient movements between the preoperative and postoperative HDU and the OR into a single location, ORBLOCK, to avoid inflating the number of transfers. For example, patient movement from a bed ward to the preoperative area, in to the OR, to the pre-/postoperative HDU, and back to the bed ward would be counted as two transfers (bed ward – ORBLOCK– bed ward), not four transfers.

Transfer patterns

We describe intrahospital transfer patterns at hospital departmental level using networks, and at individual patient level using transfer chains. In network analysis and graph theory,[13 14] a network is a graph that contains two types of elements: *vertices* (or nodes) and *edges*. A vertex represents the elementary unit of the system, and an edge captures the interaction between two different units. The edge can be directed or undirected. If two vertices are connected more than once, a weight can be assigned to the edge between them. Network *density* is defined as the ratio of the number of existing edges over the sum of all possible edges for all vertices. *Degree* of a vertex is the number of other vertices it is connected with. Taking into account whether each connected vertex is on the 'from' or 'to' side of the edge, *out-degree* and *in-degree* for a vertex can be computed.

In this study, vertices were hospital locations patients had visited, and edges were the transfers between any two locations. Imagine an emergency patient who needs surgery and therefore is transferred from the ED to a bed ward, then to the OR, then back to the same bed ward, and eventually discharged home. This transfer history can be constructed into a network of three vertices and three edges, if we ignore the final discharge to home. For each of the four departments studied, we first constructed an unweighted, undirected network to explore global connectivity, disregarding timing, frequency and type of transfers. We further constructed more detailed networks by letting them change with time, from study week 1 through 52, and from weekday to weekend. Finally, we examined the temporal frequency of specific types of transfers. Here, we categorised all edges in the networks into three broad transfer groups: *ED-Any* (transfers from the ED to any other ward), *Bed ward-Bed ward* (transfers not involving technical wards) and *Technical* (transfers involving technical wards; ie, ICUs, HDUs and ORs).

Network analysis only captures the grand total of location-to-location transfers and is insufficient to examine individual patients' transfer trajectories. We therefore extracted the transfer chain for each stay, keeping the sequence of locations. Variables of interest were the actual transfer sequences themselves and the length of the chains, that is, the number of transfers.

Network and statistical analysis

Network size was quantified by number of vertices and edges (unique locations and transfers). For the 52 weekly networks in the temporal network analyses, we report mean and SD of weekly vertex and edge counts. Network density was computed for the undirected, unweighted networks. In-degree and out-degree for vertices were computed for directed, unweighted networks in the weekday–weekend network comparison. Descriptive statistics of patient cohort characteristics are provided as counts, percentages or medians (10th–90th percentiles) as appropriate. Frequencies of the various transfer chains were examined and the most common types of chains were listed.

Two multivariate Poisson regression models were used to identify risk factors associated with higher number of intrahospital transfers. Explanatory variables used in both models were age (categorised as 18–39, 40–64, 65–84 and 85+ years), gender, admission type (elective vs emergency), departmental allocation, physiological derangement (mean first 48-hour NEWS2, categorised as 0–2, 3–4, 5–6 and 7+) and whether non-prophylactic antibiotics were administered during the stay. In the second model, we also included variables indicating treatment (having undergone surgery, having a stay in an HDU or ICU). Interaction terms between departmental allocation, surgery and antibiotic use were modelled. Results are reported as transfer rate ratios (RR) with 95% CIs. P values <0.01 are considered statistically significant.

All analyses were implemented in the statistical software R (V.3.4.2). Network analyses and visualisation were conducted using packages igraph[15] (https://igraph.org) and ggraph.[16]

RESULTS

Patient cohort and hospital locations

After processing, the cohort contained 17 198 unique records. Table 1 summarises the cohort demographics and locations visited, stratified by whether the stay involved surgery.

The gastroenterology department had fewest admissions (n=1712, 10%); the other three departments had between 4788 and 5522 admissions. Surgical procedures were rare for stays in the neurology department (1%) and common in the orthopaedics department (61%). Overall, across departments, 63%–83% of patient stays were non-elective, that is, emergency admissions starting in the ED.

The proportion of stays with non-prophylactic antibiotics administered varied from 11% (neurological patients not undergoing surgery) to 57% (gastroenterological patients undergoing surgery). Antibiotic use was more common for stays with surgery, irrespective of department. LOS and maximum NEWS2 during the first 48 hours of stay were higher in stays with surgery, except in the neurology department. Stays with surgery also on average comprised two more unique intrahospital locations and more transfers than stays without surgery (median 3 times vs 1). Overall, 0.5% of patients experienced eight or more transfers. Maximum transfer count varied markedly between the medical departments (8) and the surgical departments (23).

Transfer networks

A total of 1940 (11%) stays comprised only one intrahospital location and were excluded from network analysis. In total, 35 001 location-to-location transfers were found for the remaining 15 258 patient stays. Figure 1 displays the department-wise static networks. Vertex colours indicate ward types. In general, the ED, OR, HDUs and ICUs had many connections with wards in all studied departments. Many emergency patients ultimately allocated to one of the four studied departments were initially transferred from the ED to the OR, an HDU or one of a wide range of surgical and medical wards belonging to other departments. The orthopaedics department network was most densely connected, comprising 28 locations and 155 unique location-to-location transfer pathways, giving a network density of 0.410. The neurology department network was the least densely connected, with 20 vertices, 55 edges and network density of 0.288. Despite a much larger cohort size (4788 vs 1712 stays), the gastroenterology department had network size and density very similar to neurology.

Figure 2A visualises week-by-week edge (location) and vertex (unique transfer pathway) counts throughout the study period, stratified by hospital department. The gastrosurgery and orthopaedics networks contained many more transfer pathways than the other two departments. The orthopaedics network also displayed marked temporal variations over the year. A dip in connectivity around study weeks 3–10 could have been due to less elective surgery and closure of wards during summer holidays.

Figure 2B displays week-by-week number of transfers, stratified by transfer type and department. In figure 2C, these data are normalised by number of admissions during that week in the corresponding department. *ED-Any*-type

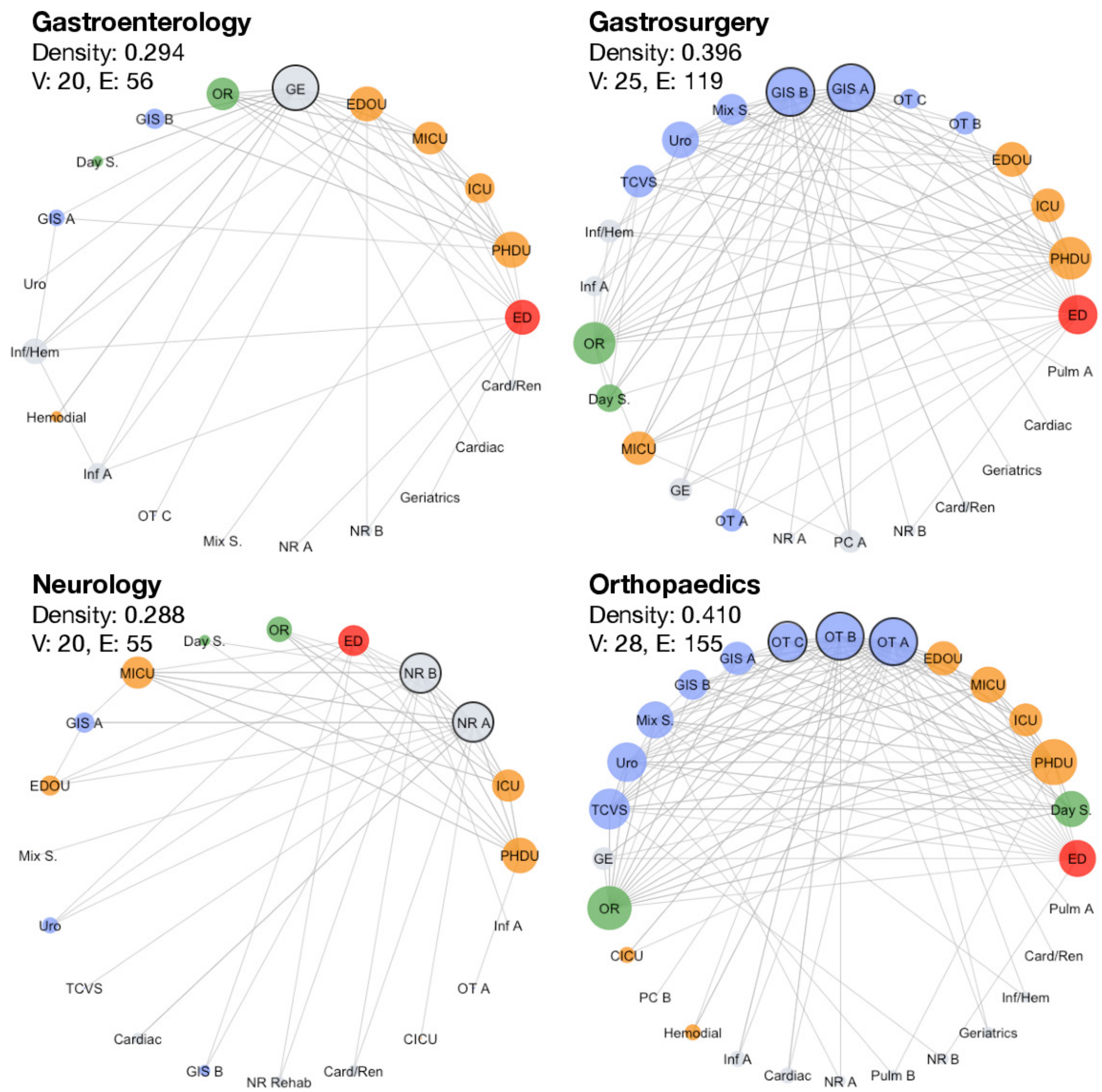

Figure 1 Unweighted, undirected patient transfer networks for four hospital departments over a 1-year period. Vertex (location) colours distinguish different functionality, that is, ED, ORs, ICUs and medical and surgical wards. Vertex size is proportional to its degree (number of other locations connected to it). Network sizes are given as edge (E) and vertex (V) counts and density. The complete list of abbreviations is found in online supplemental table S1. ED, emergency department; EDOU, emergency department observation unit; GE, gastroenterology; GIS, gastrointestinal surgery; ICU, intensive care unit; MICU, medical intensive care unit; NR, neurology; OR, operating room; OT, orthopaedics; PHDU, postoperative high-dependency unit; TCVS, thoracic and cardiovascular surgery.

transfers denote emergency hospital admissions and were relatively constant over time for all departments. The neurology department had fewest elective admissions, thus its normalised *ED-Any* was close to 1. Counts of *Bed ward-Bed ward* transfers also were rather constant and did not constitute much of the traffic. In contrast, *Technical*-type transfers, involving transfers to and from ICUs, HDUs and ORs, showed distinct temporal variation and lower activity during the summer holidays.

Network connectivity varied during the week (figure 3). On average, networks included more locations (vertices) and almost twice as many unique location-to-location transfer pathways (edges) on weekdays as during weekends. A majority of hospital locations visited by our patient cohort received patients from more locations (higher in-degree) and transferred patients to more locations (higher out-degree) on weekdays than on weekends. Adjusted for number of patients present (bed occupancy was higher on weekdays than weekends), number of transfers was still higher on weekdays. In contrast, the number of unique locations used by patients ultimately allocated to one of the four studied departments was higher on weekends.

The ED had a very large out-degree but zero in-degree, as this ward feeds patients to many locations but receives no patients from other hospital wards. Conversely, the 'home' wards for our patient cohort (gastroenterology, gastrosurgery A/B, neurology A/B, orthopaedics A/B/C) received their patients from more locations than they transferred patients to. Home wards thus 'assembled' patients from the ED, OR, HDUs and any 'ad hoc' wards, ultimately for patient discharge to home.

Zhang C, *et al*. *BMJ Open* 2022;**12**:e054545. doi:10.1136/bmjopen-2021-054545

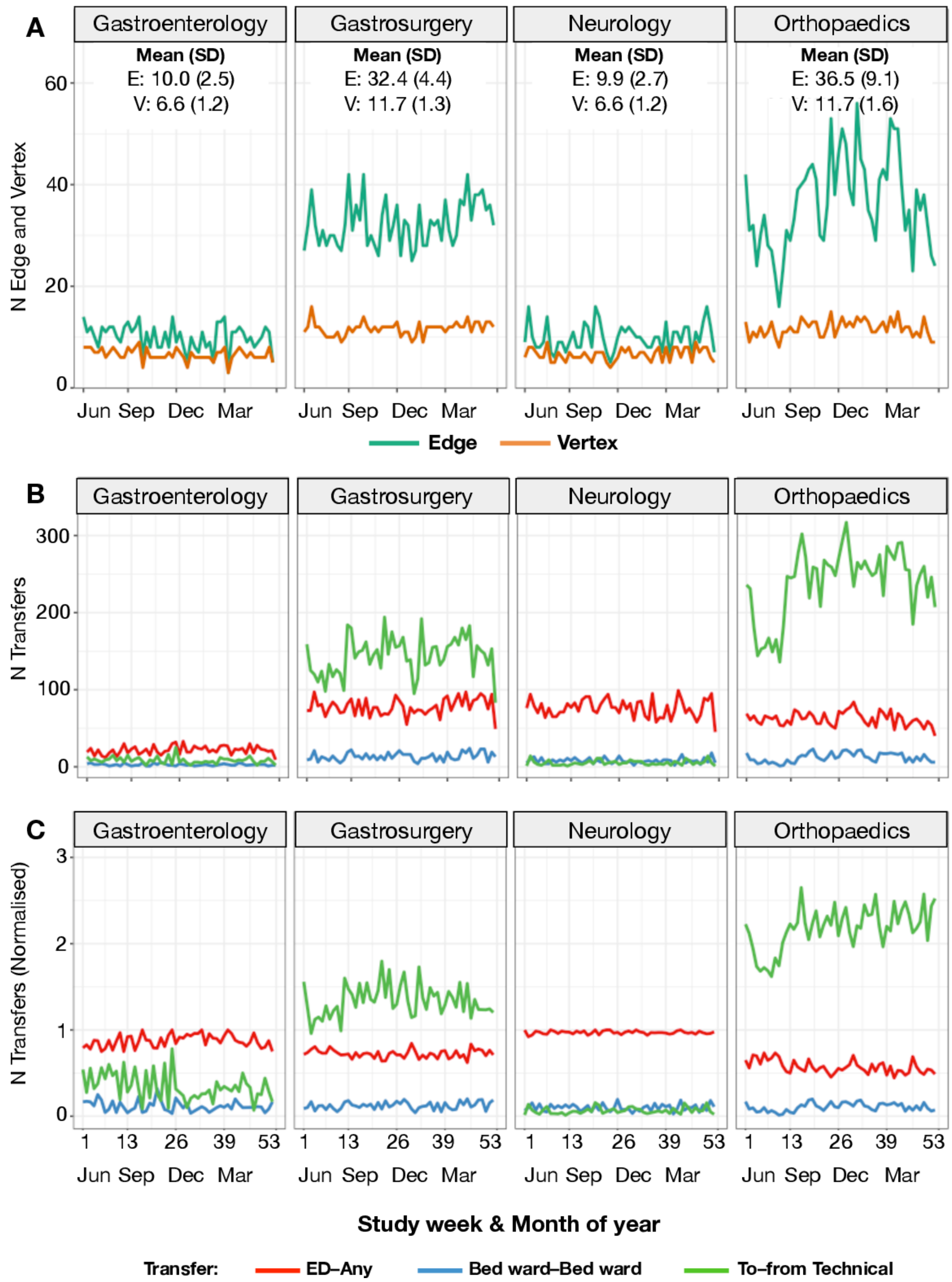

Figure 2 Temporal changes in network size by hospital department and transfer type. (A) Weekly network sizes in terms of transfer pathway (edge) and location (vertex) counts. (B) Weekly sum of transfers, split by transfer type. (C) Weekly sum of transfers by type, normalised by number of patient admissions in the corresponding department that week. Study week is counted from a Monday in June 2018; hence, study weeks 1–13 denote June to August, and so forth. *ED-Any*: transfers from the emergency department (ED) to any other ward. *Bed ward-Bed ward*: transfers between regular wards. *To-From Technical*: transfers involving technical wards, that is, intensive care units (ICUs), high-dependency units (HDUs) and operating rooms (ORs).

Patient transfer chain analysis

The 15 258 patient stays comprising more than one intra-hospital location followed 1118 unique transfer chains, that is, sequences of locations. Chain utilisation was highly skewed: 75% of transferred patients followed one of the top 20 (1.8%) transfer chains (table 2). The three most common transfer chains, from the ED to one of the two neurological bed wards or the ED observation unit, together represented one-third of transferred patients. Ten out of the 20 most common transfer chains involved only one transfer and started in the ED. The subpattern *Bed ward - ORBLOCK - Bed ward* occurred in nine out of the 20 most common transfer chains.

In contrast, the majority of unique transfer chains occurred infrequently: 10% of patient stays (1505 out of 15 258) followed one of 976 uncommon patterns (87% of all types), each occurring ≤7 times over the 1-year period. Compared with the majority, in this 10% subgroup,

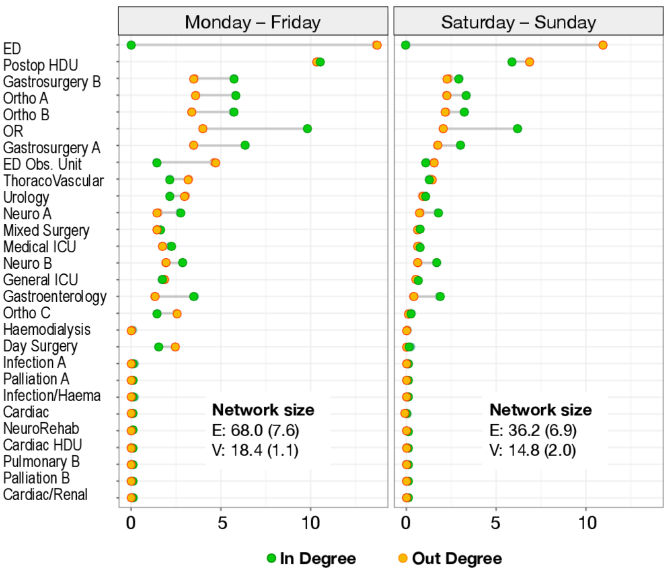

Figure 3 Transfer network connectivity on weekdays and weekends. For 30 hospital wards, daily average number of hospital locations the ward received patients from (in-degree, green dots) and sent patients to (out-degree, amber dots). Data for all stays allocated to any of the four studied departments, split by weekday/weekend. Full-year network size (all four departments) is reported as mean (SD) of edge (E) and vertex (V) counts. ED, emergency department; HDU, high-dependency unit; ICU, intensive care unit; OR, operating room.

patients stayed at a higher number of unique hospital locations (4 (2–5) vs 3 (2–3)) and more often underwent surgery (64% vs 49%) and advanced treatment in an HDU or ICU (42% vs 23%). Also, in this 10% subgroup, 8% of patient stays from the gastrosurgery or orthopaedics department also involved stays in medical bed wards, as opposed to 0% among the remaining surgical patient stays.

Two multivariate Poisson regression models identified risk factors associated with a higher number of intrahospital transfers (table 3). In the first model, older age was negatively associated with more transfers, while higher mean first 48-hour NEWS2 was associated with more transfers. The effect increased from NEWS2 scores 0–2 via 3–4 to 5–6, from where it levelled off. The effects of age and NEWS2 were no longer significant when treatment in the OR or HDU/ICU was adjusted for (model 2 in table 3). Gender did not contribute significantly in either model.

Emergency hospital admission and antibiotic use were associated with increased risk of undergoing more transfers, as was treatment in the OR or an HDU/ICU. Although much of the increased risk was explained by these factors, admission to surgical departments (gastrosurgery and orthopaedics) in itself increased the risks of more transfers. Modelled interactions between departmental allocation, surgery and antibiotic use were not significant (online supplemental table S2).

DISCUSSION

The main finding in this retrospective study applying network analysis on patient location data in four hospital departments was a marked heterogeneity in patient transfer patterns. Departments differed markedly regarding network size and density, transfer types and temporal changes over the week and year.

Why network analysis of patient location data

Given the range of health services offered to different patient populations, patient flows within hospitals would be expected to vary widely between departments and even wards. Optimisation of patient logistics is key to reduce delays and overcrowding, and thus time and healthcare costs. Availability of beds in wards specialised for each patient's medical condition likely reduces errors and improves quality of care. Detailed knowledge of highly connected hospital hubs and patient trajectories is also important for prevention and control of hospital infections.[2 3]

Heterogeneity in size and connectivity of transfer networks

In all departments studied, a majority of stays were emergency admissions via the ED. As in previous work,[1] the number of emergency admissions was relatively constant over time (figure 2B,C). The ED acted as a hub feeding patients to their allocated department's 'home' wards (figure 1). However, networks revealed that gastrosurgical and orthopaedic patients also to a large degree were treated in surgical wards in other surgical departments. 'Home' and 'non-home' wards alike transferred patients to and from the OR. Likely, the large proportion of emergency admissions at AUH intermittently caused patient surges, overcrowding and patients being placed in any suitable ward with a free bed and only later transferred to a ward in their allocated department. Gastrosurgical and orthopaedic patients, many of whom are multimorbid, also had stays in a number of medical wards (figure 1). This resulted in the two surgical departments having larger and 2.5–3 times more densely connected transfer networks than those of the two medical departments, which may have treated more homogenous patient populations. Although neurology had many more admissions than gastroenterology, the two networks were very similar in number of locations and connectivity.

These findings illustrate that patient flows in one department may be heavily affected by logistic changes implemented in seemingly unconnected departments. Weighted and directed networks would provide important additional information, useful for real-time monitoring of patient flows.

Temporal variation in patient transfer networks

Monitoring of temporal changes in patient transfer networks is relevant for capacity planning, but in-depth organisational knowledge of studied departments is required for interpretation of findings to be reliable. We saw marked heterogeneity across hospital departments

Table 2 The 20 most common intrahospital transfer trajectories

Location sequence	n	%	Cum %
ED—Neurology A	2015	13.3	13.3
ED—ED observation unit	1544	10.1	23.4
ED—Neurology B	1508	9.9	33.3
ED—Gastrosurgery A	872	5.7	39.0
ED—Gastrosurgery B	866	5.7	44.7
ED—Orthopaedics A—ORBLOCK—Orthopaedics A	474	3.1	47.8
ED—Gastroenterology A	470	3.1	50.9
Orthopaedics C—ORBLOCK—Orthopaedics C	429	2.8	53.7
ED—Orthopaedics B—ORBLOCK—Orthopaedics B	413	2.7	56.4
ED—Orthopaedics B	391	2.6	59.0
Orthopaedics B—ORBLOCK—Orthopaedics B	370	2.4	61.4
ED—Gastrosurgery B—ORBLOCK—Gastrosurgery B	349	2.3	63.7
Gastrosurgery B—ORBLOCK—Gastrosurgery B	325	2.1	65.8
ED—Orthopaedics A	324	2.1	67.9
Gastrosurgery A—ORBLOCK—Gastrosurgery A	309	2.0	69.9
Orthopaedics A—ORBLOCK—Orthopaedics A	293	1.9	71.8
ED—Gastrosurgery A—ORBLOCK—Gastrosurgery A	180	1.2	73.0
ED—Urology	154	1.0	74.0
ED—Neurology A—Neurology B	153	1.0	75.0
ED—Thoraco-vascular	118	0.8	75.8
Total: 15 258 patients	11 557	75.8	75.8

The 20 most common out of a total of 1118 transfer chains observed in all 15 258 patient stays in the departments of gastroenterology, gastrointestinal surgery, neurology and orthopaedic surgery over a 1-year study period.
ED, emergency department; ORBLOCK, preoperative/postoperative high-dependency unit stay in combination with operating room treatment.

regarding temporal variability (figure 2A). Week-to-week variation in number of transfers was much larger in the orthopaedics department than in gastrosurgery, despite the two networks having similar edge and vertex counts when averaged over the year. The contrast between the two surgical departments and neurology was pronounced.

Higher temporal variability in the orthopaedics department seemed to reside in transfers involving ORs, ICUs and HDUs (figure 2B) and partially reflected the weekly number of admitted patients (figure 2C). Both surgical departments had a drop in transfers during summer holidays, when fewer elective surgical procedures are performed. In the gastroenterology department, some change in patient logistics must have been implemented around Christmas, that is, study week 26. Similar effects of organisational changes have been reported in UK acute care data.[7]

Network connectivity also changed over the week. On average, studied hospital wards were connected to almost twice as many locations during the week than on weekends (figure 3). The 'assembling' function of 'home' wards, that is, wards belonging to the four studied departments (higher in-degree than out-degree), also was less marked on weekends. Admissions occurring on weekends have been shown to more often result in transfer to the ICU and to be associated with increased adjusted mortality rates.[17,18]

Individual patient transfer trajectories

Standardised patient trajectories facilitate hospital logistics and specialised treatment. Network analysis, however, examines the total number of transfers and does not capture their sequence in individual patients.[3,4] Moreover, in some healthcare systems, the format of patient location data does not facilitate the analysis of entire patient trajectories, and data validity may be poor.[1]

Core hospital pathways manage a majority of patients.[7] We found that 11% of stays involved only one location. A further 67% of stays followed one of 20 common patient transfer chains, half of which started in the ED and involved only one transfer (table 2).

In contrast, a substantial minority of patient stays represented a very high number of uncommon, non-standardised hospital location sequences. These uncommon transfer chains included more locations and more often multiple OR visits and ICU/HDU stays. Among the stays following the 10% least common transfer chains, 8% of patients allocated to one of the two surgical

Table 3 Poisson regression analysis on number of intrahospital transfers per stay

	Model 1			Model 2		
Risk factors	RR	95% CI	P value	RR	95% CI	P value
Age						
18–39	Reference			Reference		
40–64	0.984	0.949 to 1.021	0.405	1.017	0.980 to 1.055	0.382
65–84	**0.925**	0.892 to 0.959	<0.001	0.982	0.947 to 1.019	0.344
85+	**0.835**	0.793 to 0.880	<0.001	0.960	0.911 to 1.011	0.125
NEWS2*						
0–2	Reference			Reference		
3–4	**1.071**	1.027 to 1.117	0.001	0.984	0.943 to 1.027	0.470
5–6	**1.138**	1.051 to 1.231	0.001	0.956	0.882 to 1.034	0.270
7+	1.132	0.988 to 1.289	0.068	**0.801**	0.699 to 0.914	0.001
Gender						
Female	Reference			Reference		
Male	0.984	0.961 to 1.009	0.205	0.997	0.973 to 1.021	0.786
Department						
Gastroenterology	Reference			Reference		
Gastrosurgery	**1.679**	1.590 to 1.773	<0.001	**1.210**	1.144 to 1.280	<0.001
Neurology	1.039	0.980 to 1.102	0.199	**1.117**	1.053 to 1.184	<0.001
Orthopaedics	**2.406**	2.281 to 2.540	<0.001	**1.294**	1.222 to 1.372	<0.001
Admission						
Elective	Reference			Reference		
Emergency	**1.388**	1.347 to 1.440	<0.001	**1.834**	1.778 to 1.892	<0.001
Antibiotics†						
No	Reference			Reference		
Yes	**1.372**	1.336 to 1.409	<0.001	**1.107**	1.077 to 1.138	<0.001
Been to OR‡						
No				Reference		
Yes				**2.936**	2.846 to 3.029	<0.001
Been to ICU§						
No				Reference		
Yes				**2.106**	2.025 to 2.189	<0.001

Bold font indicates a statistically significant association with number of transfers per stay.
*Mean first 48-hour NEWS2 score.
†Use of any non-prophylactic antibiotics.
‡Indicates a surgical procedure.
§Stayed in an ICU or HDU, indicates a severe patient condition.
HDU, high-dependency unit; ICU, intensive care unit; NEWS2, National Early Warning Score 2; OR, operating room; RR, rate ratio (patient transfer).

departments (orthopaedics or gastrosurgery) also had stays in medical bed wards. In contrast, surgical patients following the 90% most common transfer chains had no medical ward stays. Multimorbidity thus seemed to predispose for non-standard needs, which again is known to carry a higher risk of unwanted outcomes.[3–6]

Although not necessarily causal, the factors associated with higher number of intrahospital transfers in our regression analysis are clinically recognisable as proxy variables for more complex hospital stays. Caution must be used when interpreting effect sizes, since there could have been interdependence between variables. The regression model controlling for age and gender showed an increase in number of transfers with increasingly deranged physiological state early in the hospital stay, quantified as mean NEWS2 during the first 48 hours. The effect levelled out at NEWS2 of 5 or higher; values that are often associated with transfer to more advanced care.[12] In the model that also adjusted for treatment in an HDU, ICU or OR, the statistical contribution of NEWS2 was no longer detectable. The effect of these two variables could thus not be disentangled by our analysis.

Non-prophylactic antibiotic use was associated with more patient transfers. This variable could have acted as proxy for bowel anastomosis leakage or postoperative wound infections needing repeated surgical treatment, and postoperative pneumonia needing advanced monitoring or mechanical ventilatory support. Interestingly, stays in surgical departments were associated with increased number of intrahospital transfers even after statistical adjustment for clinical risk factors, OR and ICU treatment.

Implications for clinicians and policymakers

Analysis of intrahospital patient transfer networks is relevant for design of new hospital buildings and allocation of hospital areas for essential units acting as hubs. Proximity between wards frequently connected by transfers may increase efficiency. In wards with known high connectivity, planning more isolation beds might be prudent, to shield vulnerable individuals and prevent outbreaks.

Ongoing monitoring of the connectivity (in-degree and out-degree) of individual hospital wards is highly relevant for infection prevention and control. When new pathogens emerge simultaneously in different wards with no apparent linkage, network and transfer sequence analysis may reveal possible transmission routes that can be controlled. To limit a hospital outbreak, it may be useful to identify units so frequently connected by transfers that they should be regarded as equally exposed to an infectious agent.

Patient transfer is often necessary for diagnostics or specialised treatment, but intrahospital transfers may also result from foreseeable and preventable factors such as seasonal overcrowding and staffing shortages, construction work or wards being closed during infection outbreaks. Evaluation of factors resulting in transfer peaks might motivate improved institutional preparedness. Placing patients in inappropriate specialty areas increases the risk of medical errors when staff are exposed to unfamiliar medical conditions, treatments or devices. Real-time transfer analysis may identify and warn hospital managers about unusual, potentially high-risk transfer sequences.

The methods applied in this study could be used to monitor patient flows, predict likely logistic problems and routes of infection spread and develop plans for optimising placement of patients deemed at risk for long and complicated hospital stays. There is a need for standardised indicators of patient flow logistics to facilitate comparison between institutions and health systems.[1]

Strengths and limitations

A 1-year study period prevented the analysis of long-term trends. We only had data for adult patients allocated to four selected hospital departments. Short-term patient movement, for example, for medical imaging or diagnostic procedures was not studied. Generalisability of our findings may be limited to similar healthcare systems.

Strengths of this study include that complete data sets with a high time-resolution, comprising both elective and emergency admissions, were evaluated on a departmental and ward level. Transfers were categorised by subtype, and individual transfer trajectories were associated with key clinical patient characteristics. Our methodological approaches should be transferable to new settings.

CONCLUSION

Temporal network analysis applied on departmental and ward levels provides insight into the heterogeneity of intrahospital patient transfers. The method is a potential tool for continuous, automated monitoring of patient flows. Analysis of typical and atypical patient transfer trajectories is a useful supplement. Obvious areas of benefit are hospital capacity management across wards and departments, and infection prevention and control.

Areas remaining for future research include patient and systemic factors that may predict and prevent extremely long transfer trajectories. Frequent changes of intrahospital location may negatively affect important aspects of patients' experience of their care, such as quality and consistency of medical information given and confidence in hospital staff.[19] Intrahospital transfer patterns should therefore be studied also in view of patient-reported outcome measures.

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Acknowledgements Haldor Husby at the Akershus University Hospital's Department for Data Extraction and Analysis provided invaluable assistance.

Contributors MT and TE devised the overall project. TE defined the data set, oversaw data extraction and interpretation and contributed to data restructuring. SS and SBJ conceptualised the study. CZ designed the data analysis plan, cleaned and analysed the data, made all the figures and created the tables. CZ and SS interpreted the results and drafted the manuscript. MT oversaw the analysis and interpretation. All authors critically evaluated and discussed the ongoing analyses, critically revised the manuscript and approved the final version. CZ and SS are guarantors of the study.

Funding Norwegian Research Council (CZ)—BigInsight project (grant number 237718); University of Oslo (TE, MT, SS); Akershus University Hospital (SBJ, SS).

Competing interests None declared.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Patient consent for publication Not required.

Ethics approval This study involves human participants and was approved by the Regional Committee for Medical and Health Research Ethics (REK SørØst C reference number 33192) and was considered exempt from patient consent requirements by the AUH institutional Data protection officer (reference number 2019/56). The study was considered exempt from patient consent based on the study being (1) solely observational, (2) retrospective, (3) only using data that had

been routinely collected for administrative or routine clinical use, (4) involving a large number of patient stays (a 12-month cohort; >17 000 stays), and (5) data were released to the authors without specified time stamps for further anonymisation, Akershus University Hospital retaining all patient identifiers.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available upon reasonable request. The data that support the findings of this study are deidentified patient records from Akershus University Hospital's (AUH) Department for Data Extraction and Analysis. Due to Norwegian legislation restrictions apply to their availability. The data were used under licence for the current study and so are not publicly available. Data are however available from the authors upon reasonable request, provided that permission is obtained from the South-East Norway Regional Committee for Medical and Health Research Ethics and the AUH Data Protection Officer for Research.

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