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Method to apply temporal graph analysis on electronic patient record data to explore healthcare professional–patient interaction intensity: a cohort study

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ABSTRACT

Aim Interactions between patients and healthcare professionals (HCP) during hospital admissions are complex and difficult to interrogate using traditional analysis of electronic patient record (EPR) data. The objective of this study was to determine the feasibility of applying temporal network analytics to EPR data, focusing on HCP–patient interactions over time.

Method Network (graph) analysis was applied to routinely collected structured data from an EPR for HCP interactions with individual patients during admissions for patients undergoing renal transplantation between May 2019 and June 2023. Networks were constructed per day of admission within a session, defined by whether the patient was in the intensive care unit (ICU) or standard hospital ward. Connections between HCP were defined using a 60 min period. Reports were generated visualising daily interaction network structures, across individual admissions.

Results 2300 individual networks were constructed from 127 hospital admissions for renal transplantation. The number of nodes or HCP per network varied from 2 to 45, and network metrics provided detail regarding variation in the density and transitivity, changes in structure with different diameters and radii, and variations in centralisation. Each network analysis metric has a contribution to play in describing the dynamics of a daily HCP network and the composite findings provide insights that cannot be determined with standard approaches.

Conclusions Network analysis provides a novel approach to investigate and visualise patterns of HCP–patient interactions which allow for a deeper understanding of the complex nature of hospital patient care and could have numerous practical operational applications.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Network analytics can be used to assess healthcare professionals (HCP) team dynamics using routinely collected electronic patient record (EPR) data. Existing studies have investigated collaboration structures of HCPs within a department or over a single admission, concentrating on the collaboration between HCPs rather than overall HCP interactions with patients.

WHAT THIS STUDY ADDS

⇒ Network analytics relating to HCP–patient interactions, derived from routine EPR data, can be determined for individual patients for each day of their hospital admission. This allows for the construction of temporal networks across a hospital admission, which may provide novel insights for the delivery of clinical care and patient safety.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ Our method allows scalable, reproducible and detailed evaluation of patient interactions with HCP throughout their stay in the hospital. This method may both improve the ability to predict HCP resourcing for given procedures and detect atypical interaction patterns, thus aiding resource planning and acting as a novel marker of clinical complexity and safety.

INTRODUCTION

The interactions between patients and healthcare professionals (HCP) within a hospital admission are complex and difficult to navigate using traditional analytical approaches.[1] The interactions between HCP and patients could serve as an important signal to assess the quality of care and patient safety. To assess the intensity of care by HCP for an individual patient the connectivity between HCP needs to be measured.

The objective of this study was to determine the feasibility of applying temporal network analytics, focusing on the changing connections between HCPs over time, to provide a deeper understanding of the HCP-patient interactions as they fluctuate during a hospital admission.

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Electronic patient record (EPR) systems have been developed to capture as much data about an individual patient's interactions with a hospital as possible.[2] Every HCP–patient interaction from the administering of a medication to the writing up of clinical notes, is recorded with an individual HCP identifier and a datetime stamp. From a data science perspective, the primary advantage of an EPR system is that all this patient data is brought together in a consistent structure. However, this structure is predominately in the form of relational databases and is not structured to readily investigate the connectivity between all the data recorded. HCP activities are generally dispersed across several tables each recording specific activities. Even within a particular table, determining HCP interactions requires a self-referential relationship, which is difficult to achieve within a relational database.

By using data engineering techniques, the source data can be re-structured into a non-relational network database. With this restructured data, network analytics with its focus on the relationships between data items, can be used to distinguish different HCP collaboration networks, where two or more HCP work together and HCP interaction network structures with individual patients.

Existing studies have investigated the collaboration structures of HCPs within a department or over a single admission Zheng *et al*,[3] Malin *et al*[4] and Soulakis *et al*.[5] However, to the best of our knowledge, only one study, Durojaiye *et al*,[6] has considered the changing daily structures for an individual patient as they progress through an admission.

The present study, by creating daily HCP collaboration networks for individual patients, enables network metrics to provide measures of continuity and intensity of care and how that varies from day-to-day, for each patient facilitating a temporal network visualisation.[7]

We considered a real-world example involving patients undergoing a single procedure, with admission for live-related or deceased donor kidney transplantation. This procedure was chosen because patients are generally brought in specifically for this procedure and discharged on their successful recuperation, without involving other major procedures (unless complications occur within the same admission).

METHOD

Data source and population

This retrospective study was conducted at Great Ormond Street Hospital for Children NHS Foundation Trust (GOSH) in London, UK using a nephrology dataset. GOSH has been using the Epic EPR system since April 2019.[8] Data for this study was extracted from GOSH's EPR data warehouse (Epic's Caboodle) and the de-identified dataset accessed via the organisation's secure digital research environment (DRE). The example cohort was defined as admissions for patients who had undergone the same principal procedure of The International Classification of Diseases, Tenth Revision (ICD-10) H01.2, 3, 4 or 5, allotransplantation of the kidney.

The GOSH DRE has predefined data pipelines that produces standard tables (research data views; RDV) for any clinical cohort. RDV are two-dimensional datasets that cover most data requirements of the clinical research teams at GOSH and represent a functional union of data from several source tables. The primary RDV used for this study was the HCP RDV (table 1). All the recorded actions have a linked de-identified patient ID, HCP ID representing the HCP who carried out the action and a start and end timestamp. Additional RDV used to supplement the HCP RDV were patient demographics, hospital admissions, ward stays and theatre list.

Creating the graph

For speed of processing, a single data view was created from the constituent RDV. The core of the data view was the HCP RDV. Additional columns were then added from the hospital admission, specifically, admission and discharge dates, and from ward stays and whether the event was in a non-intensive care unit (ICU) or ICU ward. Hospital admissions were subdivided into sessions based on ward movements in and out of the ICU. Sessions were split into days, such that a full day would be from 00:01 to 24:00. There are a significant number of 'days' when a patient was admitted, discharged, or moved in and out of the ICU meaning the 'day' was less than 24 hours. To incorporate these days this study defines a 'day', for comparison purposes, as being 16 hours or longer but <24 hours owing to the relatively high number of subdivided days due to admission, discharge and ward movement events.

HCP networks were created for each patient, hospital admission, session and day. HCP networks were created by defining all unique HCP interacting with a patient, within a session, as nodes. A glossary describing all graph analysis terms used in this paper both in general terms and specifically how they relate to HCPs temporal networks has been included at the end of this paper. For each node, the HCP's description, their professional group and the number of actions performed were defined as parameters. An edge represents at least one occurrence of two HCPs that carried out any activity for a given patient within a 60 min period at any time during the day (eg, two HCP one administering a medication and another conducting a blood test). A 60 min period, rather than the complete day, was chosen by discussion with clinicians to enable a measure of the intensity of care. Multiple interactions between the same HCPs were recorded and used as the weight of the edge (eg, the same two HCP then conducting additional laboratory tests). Once each network was created, network analytical metrics were calculated and recorded in the admission json file for use in the visualisation stage. Full definitions of the network metrics used can be found in Newman 2nd,[9] with additional material specific to 'Network in People Analytics'.[10]

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Table 1 Break down of professional actions by EPIC Caboodle source table and action type used in the healthcare professionals research data views

Action source	Action type	Professional group	Actions	HCPs
ClinicalNoteFact	Authoring	AHP	1662	117
		Medical	6725	592
		Nursing	5096	461
		Other	711	124
DiagnosisEventFact	Entered	Medical	109	40
		Nursing	6	4
	Removed	Medical	27	18
		Nursing	1	1
FlowsheetValueFact	Taken	AHP	4751	134
		Medical	19 901	297
		Nursing	1 177 061	578
		Other	85 539	143
LabTestFact	Collected	AHP	39	13
		Medical	1888	93
		Nursing	23 923	249
		Other	857	57
MedicationAdministrationFact	Administering	AHP	13	7
		Medical	3563	175
		Nursing	27 356	305
		Other	4	3
MedicationOrderFact	Ordered By	AHP	1835	44
		Medical	12 417	473
		Nursing	768	89
ProcedureEventFact	Anaesthesia	Medical	149	44
	Performing	Medical	830	145
		Nursing	3	3
ProcedureOrderFact	Ordered By	AHP	203	35
		Medical	11 168	363
		Nursing	18 839	261
		Other	437	55
VisitFact	Primary	AHP	4	3
		Medical	56	36
		Other	1	1
	Second	AHP	1	1
		Medical	23	18
		Nursing	19	6
	Third	Medical	6	6
		Other	1	1
	Fourth	Medical	1	1

AHP, allied health professional; HCPs, healthcare professionals.

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The first metric is the number of nodes in a network which represents the number of HCP.

Outputs

For each patient hospital admission, two reports were produced. The first report was a hospital admission view in the form of an Excel spreadsheet with sheets including: (1) Hospital admission—summary details of the patient and admission; (2) sessions—summary graphs for each session; and (3) session days—summary graphs for each day in 7-day blocks repeated for full admission with a change of sheet when the session changes. The second report was a more detailed view of the same hospital admission. For each HCP network there is a full-scale graph visualisation, detailed node tables sorted by different centrality types, edge details, events summarised by the professional groups and all procedures performed on the given day.

Tools, data transformation and code availability

The code for this study was developed using Python (V.3.8). The two primary packages used were pandas (V.2.0.1),[11] for data frame input, manipulations and output and iGraph (V.0.10.4),[12] for creating and visualising networks and returning network metrics. The iGraph package for Python does not include centralisation metrics which were separately coded in Python based on Freeman's equations.[13] The major stages in the process included: Loading extended CSV file, including admission and session data; filtering by patient and session or session day; processing filtered data frame to generate a unique list of nodes, store as dictionary, iterate through data frame and create list of edges; graph creation using node dictionary and edge list and record graph, node and edge metrics in dictionary; storing of results, all sessions and sessions days, in json file for each patient admission; output creation using metrics stored in json file (detailed HTML document with network plots created in two sizes of image and admission summary using Excel spreadsheets with multiple sheets linked to images created in the previous step).

RESULTS

There were 127 hospital admissions, 5 had cancelled procedures due to the donor or recent factors, in the period May 2019 to October 2023 involving 122 patients,

Table 2 Hospital admission metrics

Admission type	Admissions	Admissions %
Elective – planned	69	54.33
Emergency	34	26.77
Elective – waiting list	21	16.54
Elective – booked	3	2.36
Number of ICU stays (within an admission)	Admissions	Admissions %
0	85	66.93
1	41	32.28
2	1	0.79
Principal procedures (OPCS-4)	Admissions	Admissions %
M01.2 – allotransplantation of kidney from liver donor	107	87.70
M01.4 – allotransplantation of kidney from cadaver heart beating	11	9.02
M01.5 – allotransplantation of kidney from cadaver heart non-beating	4	3.28
Length of stay (days)	Admissions	Admissions %
7–10	46	36.22
11–20	54	42.52
21–30	13	10.24
31–	9	7.09
Age group on admission (years)	Admissions	Admissions %
0–2	5	4.10
3–5	16	13.11
6–11	42	34.43
12–17	59	48.36

ICU, intensive care unit; OPCS-4, Office of Population Censuses and Surveys Classification of Interventions and Procedures version 4.

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1932 individual HCP and 1.4 m recorded HCP patient interactions (table 2). HCP interactions classified by professional group are shown in table 1. The 'Action Source' represents the source tables that recorded the HCP patient interactions, with the Action Type, used to differentiate multiple professionals on a single record. The table also details the number of individual patients and admissions that were involved.

80 admissions had a single session, 41 admissions had three sessions with a single stay in ICU and 1 admission had five sessions, with two stays in ICU. 207 session graphs were created. 2083 session day graphs were created, of these 1849 (88.7%) were of a session of greater than 16 hours long. Of the 1849 sessions 38 (2.0%) were in ICU.

Figure 1 shows a comparison between an HCP network for a complete patient admission and the individual daily networks for the same patient admission. Nodes represent individual HCP and, node size represents the number of actions undertaken by a given HCP for that patient. An edge represents at least one occurrence of two HCP that carried out an activity for the given patient within a 60 min period, at any time during the day. Figure 2 shows an example of the hospital admission session days sheet. Each session day HCP network is shown with its graph level metrics, the number one ranked node for each node centrality type, a breakdown of the events performed that day and the principal procedures performed were appropriate. Cells for each numerical network metric also include heat map colouring, to visualise the relative movements of each network metric across the whole admission.

Figure 3 shows how network level metrics vary in relation to the number of nodes or HCP. Apart from the number of edges and the maximum degree, the metrics can be seen, using the Pearson correlation coefficient, to be independent of the number of nodes.

The network for a complete admission, or session, can be represented as HCP patient interaction networks for each day such that variation in the intensity of patient care from day-to-day can be visualised. The number of nodes or HCP is just the starting point. The network metrics also provide variation in the density for the same number of nodes, changes in structure with different diameters and radii and finally the construction of the network with variations in centralisation.

A single example admission (as visualised in figure 1) is described here to illustrate how network metrics combine to describe individual HCP interaction networks across an admission.

Day 1, the day of admission and the procedure had both the maximum number of nodes and edges, but also higher than average density and transitivity showing a generally tightly connected network. The diameter of 3, and radius of 2, indicates that there are members of the team less connected (ie, not having an activity within 60 min of any other HCP), reducing the intensity of care of the patient. A high eigenvector centralisation indicates that there are a few key HCP on this day, the low closeness centralisation also indicates the tightly connected nature of much of the network.

Days 2, 3 and 4 show a drop in the number of HCPs on each day from day 1, but the number of edges is still relatively high. The density and transitivity are also slightly reduced showing the reduced intensity from day 1.

Day 5, 6 and 7 show an additional drop in both nodes and edges and a corresponding drop in density, as the care reduces in intensity. As the networks decrease in size, an increase in the diameter and closeness centralisation indicates a more disparate network. This feature is combined with an increase in the eigenvector and betweenness centralisations showing that there are key HCP who are interacting with the whole HCP network on a given day.

Finally, days 8 and 9, show an increase in the HCP network intensity as the patient is prepared for discharge from the hospital. Day 8 shows a more disconnected network, with a radius of 0, indicating that some HCP are not overlapping with the rest of the team.

Each of the network analytical metrics has a contribution to play in describing the dynamics of a daily HCP network. No single metric can be used to understand these dynamics, the contribution of all the metrics is required to get a complete picture.

DISCUSSION

The findings of this study have demonstrated that the variation in the structure of HCP daily networks, as described by their network metrics, can be used to visualise the changes in a patient's intensity of care during a hospital admission.

By breaking down admission-based HCP patient interaction networks into daily networks opens up the possibility of investigating a number of issues in more depth. Two key areas for further study would be issues related to weekday versus weekend working patterns: second, comparisons of the intensity of care and its relationship to the prediction of length of stay post procedure. Care must be taken when considering this level of analysis that patients are at similar stages of their care when compared.

Previous publications on the theme of HCP collaboration and patient interaction such as Zheng *et al*,[3] Malin *et al*[4] and Soulakis *et al*,[5] are focused on organisational structures, applying analytical techniques developed for social media to apply to the collaboration structures of HCPs in a hospital.

Later publications began to focus on the level of care patients were being given, Yao *et al*,[14] considered a random cohort of 100 patients and demonstrated that graph analysis could distinguish different care patterns for individual patients. This study also considered the different graph analytical metrics and how they could be used to indicate different aspects of care. Kim *et al*[15] compared directly care patterns with length of stay.

Yan *et al*[16] compared the level of care of patients with and without COVID-19 in the ICU. This study used events

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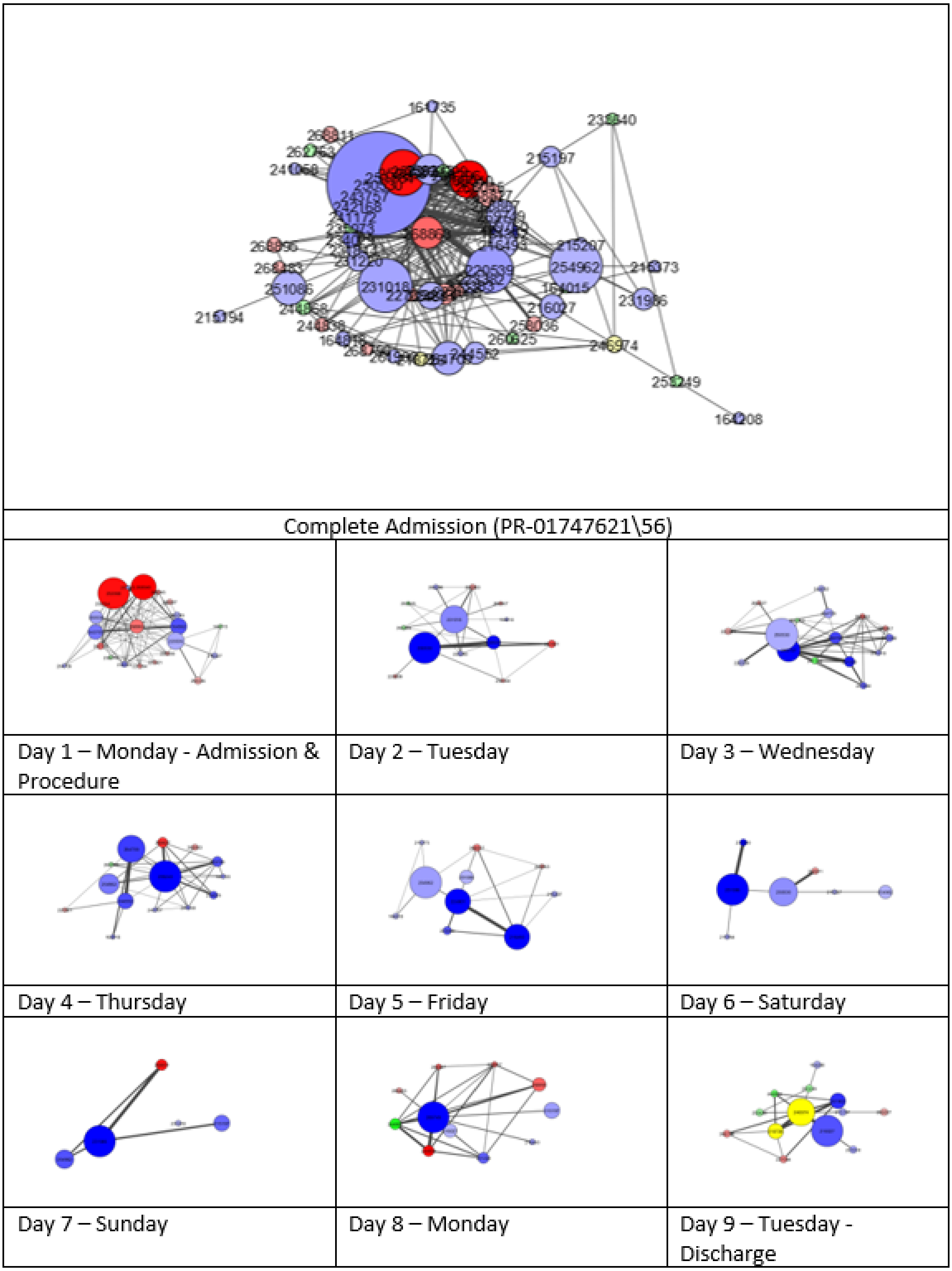

Figure 1 A comparison between an HCP network for a complete patient admission and the individual daily networks for the same patient admission. Nodes represent individual HCP, node size represents the number of actions undertaken by the given HCP for that patient, node colour represents the professional group (medical (red), nursing (blue), allied health professional (green) and other (yellow)). An edge represents at least one occurrence of two HCP that carried out an activity for the given patient within a 60 min period at any time during the day. HCP, healthcare professional.

from their EPR system but differentiated between proactive events, for example, clinical notes, medication and laboratory orders and reactive, events such as medication administrations focusing on the former and ignoring the latter. Zhu *et al*,[17] took a similar approach by splitting their HCPs into core teams, support teams and administrative

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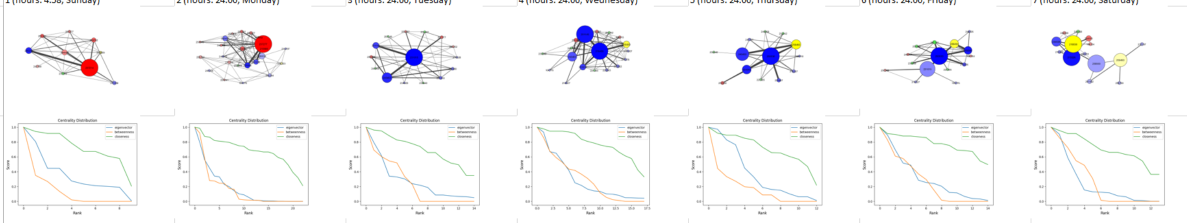

key	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
day_of_stay	1 (hours: 4.58, Sunday)	2 (hours: 24.00, Monday)	3 (hours: 24.00, Tuesday)	4 (hours: 24.00, Wednesday)	5 (hours: 24.00, Thursday)	6 (hours: 24.00, Friday)	7 (hours: 24.00, Saturday)
Graph							
Centrality							
number_of_nodes	10	23	15	18	13	15	14
number_of_edges	31	74	36	52	25	30	24
max_degree	8	14	14	14	10	10	8
density	0.689	0.292	0.343	0.34	0.321	0.286	0.264
transitivity	0.82	0.582	0.502	0.513	0.474	0.485	0.419
diameter	3	3	2	3	3	3	5
radius	2	2	1	2	2	2	3
largest_clique_size	6	7	5	5	5	5	4
number_clusters	1	1	1	1	1	1	1
Centrality - Rank 1/Centralization							
degree	Medical-Fellow-Paediatrics	Medical-Fellow-	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode	Other-Healthcare Assistant-Nursing Episode
	0.25	0.377	0.758	0.544	0.606	0.495	0.41
eigenvector	Medical-Fellow-Paediatrics	Medical-Anaesthetist-Anaesthetics	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode	Other-Healthcare Assistant-Nursing Episode	Nursing-Registered Nurse-Nursing Episode	Other-Healthcare Assistant-Nursing Episode
	0.773	0.888	0.811	0.776	0.72	0.772	0.871
betweenness	Medical-Fellow-Nephrology	Medical-Fellow-Paediatrics	Medical-Consultant-Nephrology	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode
	0.41	0.453	0.389	0.231	0.532	0.355	0.416
closeness	Medical-Fellow-Nephrology	Medical-Fellow-Paediatrics	Medical-Consultant-Nephrology	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode	Nursing-Registered Nurse-Nursing Episode
	0.019	0.009	0.009	0.006	0.007	0.007	0.015
Events (per hour)							
ClinicalNoteFact-Authoring	0.22	0.75	0.38	0.46	0.38	0.25	0.21
FlowsheetValueFact-Taken	0.87	3.5	3.46	4.17	2.71	2.58	1.88
LabTestFact-Collected	1.53	0.33	0.71	0.38	0.17	0.08	0.04
MedicationAdministrationFact-Administering		0.71	0.88	0.75	0.5	0.33	0.38
MedicationOrderFact-OrderedBy	1.53	1.04	0.25	0.42	0.08	0.04	0.04
ProcedureEventFact-Performing	0.22	0.21					
ProcedureEventFact-Anesthesia		0.04					
ProcedureOrderFact-OrderedBy	3.28	1	0.62	0.62	0.25	0.21	0.08
VisitFact-Primary	0.44						
total_events	8.08	7.58	6.33	6.79	4.08	3.5	2.62
RDV Events							
Principal procedures		M014:Allotransplantation of kidney from cadaver heart beating					
Theatre list		VCB TH 01:M01.2:Allotransplantation of kidney from live donor					

Figure 2 Patient hospital admission—example week. The heat maps work from left to right and visualise the relative movements of each network metric and the type of events being carried out with the patient.

teams. Kahn *et al*[18] was focused on collaboration at the patient bedside, meaning that medication administrations and laboratory test collection were the type of event used.

Little temporal analysis has taken place within this theme with one exception Durojaiye *et al*[6] considered the diurnal differences in multidisciplinary care teams.

It should be noted that this method is highly applicable to any healthcare site running an EPR system that incorporates a pipeline for data extraction for research. The base data structure for creating the daily networks could be as simple as patient ID, HCP ID, professional's professional group and the datetime stamp of the action. This minimum data requirement should be available from any EPR system irrespective of its vendor or common data model (eg, Observational Medical Outcomes Partnership Common Data Model (OMOP CDM) or RDV).

This base data structure represents a bi-partite graph with patients and professionals representing the two node sets and the datetime stamp creating the edge. The monopartite network required for the analysis is simply a projection of the bi-partite network, using the 60 min period as the inferred relationship. This projection would be difficult to achieve with a traditional database approach as this is a self-referencing relationship.[19]

Similarly, the coding for this project was completed in Python and iGraph but similar results could be achieved using the networkX package[20] or other programming environments (such as R), or the graph data science module in Neo4j.[21] The network metrics used to distinguish the different network structure are the base metrics available in any network analysis environment.

The current study describes a novel and generalisable method that can be applied to routinely collected EPR data extracted for research using graph analytics, with a proof-of-concept demonstrator and associated metrics. It also provides a data-driven approach to explore wider clinical and operational applications within a healthcare setting. For example, determining expected HCP interactions by day following a procedure, in order to optimally plan staffing and resource allocation; identifying deviation(s) from normal HCP—patient interactions for early identification of potential complications for risk of increased length of stay; HCP interaction patterns as markers of adverse events or for additional monitoring and understanding of infectious disease outbreaks within hospital areas.

By breaking down admission-based HCP patient interaction networks into daily networks opens up the possibility of investigating a number of issues related to weekday versus weekend working patterns. Care must be taken when considering this level of analysis that patients are at similar stages of their care when compared.

Further research is required to understand the optimal interpretation of analytical metrics in this context and to determine interaction patterns across a range of clinical scenarios. Nevertheless, the general approach described is applicable irrespective of a particular EPR system, and is potentially scalable independently of healthcare system, geography, patient group or population. It is anticipated

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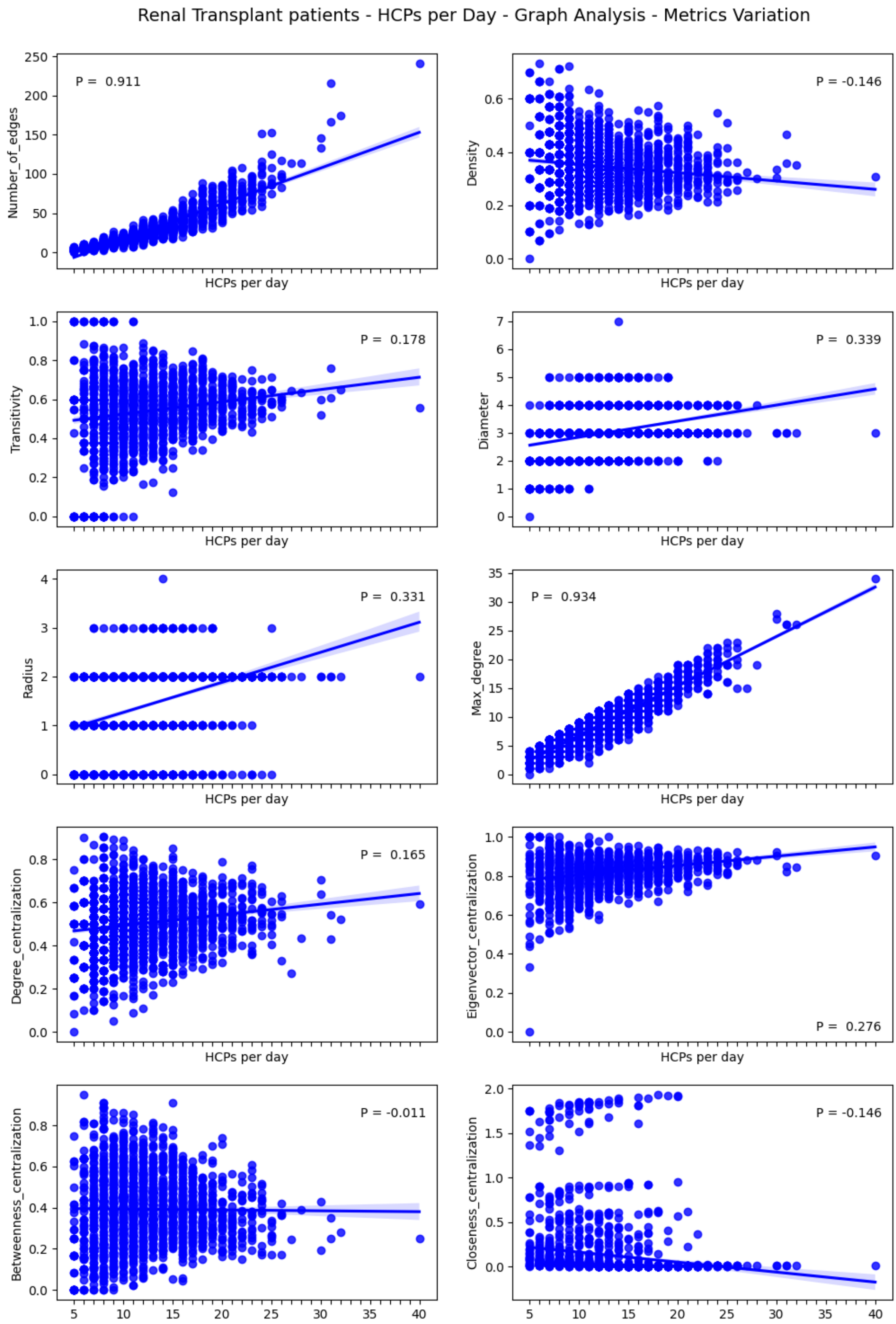

Figure 3 Variation in network level metrics by number of nodes, HCPs. Each chart represents a different network metric, edges, density, transitivity, diameter, radius, max degree, degree centralisation, eigenvector centralisation, betweenness centralisation and closeness centralisation. The Y axis being the metrics value and the X axis on all charts is the number of HCPs (nodes) per day. The charts demonstrate, using a linear regression model fit and a Pearson correlation coefficient, that these metrics are independent of the number of nodes apart from edges and max degree, so the contribution of all the metrics is required to get a complete picture of an individual network's dynamics. HCP, healthcare professional.

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that the use of graph analytics will become standard practice for investigation of multiple issues in relation to healthcare and provides an additional approach to address specific questions that are difficult or impossible to determine using other methods.

A limiting factor of this study is that the HCP—patient interactions are restricted to those recorded in the EPR system. There are two main areas of missing data one that can be more readily incorporated than the other. The first set of actions are the use of the EPR system when no data is initiated, for example, the reading of clinical notes, or just generally reviewing a patient's notes without initiating a specific action. Access to the audit log of the EPR system may be able to address this area of missing data. The second area are interactions that do not involve the EPR system, for example, face-to-face conversations about a patient, multidisciplinary team meetings or visits to the patient's bedside.

This study has focused on the visual analysis of HCP networks. The results of the study are likely to be of significant interest for multiple applications related to categorising the types of care given to an individual patient, using the variation in HCP network structure. Another area of interest could be to process the data for an individual admission as a single temporal network analysis. This approach is fundamentally different from standard database methods since it uses the relationship between the daily HCP networks, and further work will determine usefulness and applicability across a range of clinical scenarios.

CONCLUSION

Network analysis at the level of the individual patient for a given day during a hospital admission provides a novel way to use event-based EPR data to visualise differing collaboration and interaction network structures of HCPs providing direct care in an acute setting which could be used to gain a deeper understanding of the complex nature of paediatric patient care and augment the traditional analysis of patient care.

This study has demonstrated that each of the network analytical metrics contributes to a description of the dynamics of daily HCP—patient interactions. No single metric can be used to understand these dynamics, so the contribution of all the metrics is required to get a complete picture.

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