

Identifying ICU admission decision patterns in a '20-questions game' approach using network analysis

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Background. The complex intensive care unit (ICU) admission decision process has numerous non-linear relationships involving multiple factors. To better describe and analyse this process, exploration of novel techniques to clearly delineate the importance and interrelationships of factors is warranted. Network analysis (NA), based on graph theory, attempts to identify patterns of connections within a network and may be useful in this regard.

Objectives. To identify patterns of ICU decision-making pertaining to patients referred for admission to ICU and to identify key factors, their distribution, connection and relative importance. The secondary aim was to compare subgroups as per decision outcomes and case labels.

Methods. NA was performed using Gephi software package as a secondary analysis on a dataset generated from a previous study on ICU admission decision-making process using a 20-questions game approach. The data were standardised and coded up to a quaternary level for this analysis.

Results. The coding process generated 31 nodes and 964 edges. Regardless of the measure used (centrality, prestige, authority and hubs), properties of the acute illness, progress of the acute illness and properties of comorbidities emerged consistently as among the most important factors and their relative rankings differed. Using different measures allowed important factors to emerge differentially. The six subgroups that emerged from the modularity measure bore little resemblance to traditional factor subgroups. Differences were noted in the subgroup comparisons of decision outcomes and case prognoses.

Conclusions. The use of NA with its various measures has facilitated a more comprehensive exploration of the ICU admission decision, allowing us to reflect on the process. Further studies with larger datasets are needed to elucidate the exact role of NA in decision-making processes.

Keywords. critical care; intensive care unit; ICU admission; network analysis; ICU decision-making; 20-questions game.

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Contribution of the study. We performed a novel analysis of a complex decision-making process that allowed for comparison with traditional analytic methods. It allowed for identification of key factors, their distribution, connection and relative importance. This may subsequently allow for reflection on difficult decision-making processes, thereby leading to more appropriate outcomes. Moreover, this may lead to new considerations in developing decision support systems such as the formulation of pro-forma data-capture tools (e.g. referral forms). Further, the way factors have been traditionally subgrouped may need to be reconsidered, with different subgroups being partitioned to better reflect their connection. This study offers a good basis for more advanced future studies in this area to use a new variety of analytical tools.

Decision-making is the cognitive process of identifying and choosing between a number of options of varying probabilities by sufficiently reducing their uncertainty according to one's preferences, values and goals, with a resultant outcome that always involves risk.^[1-4] In critical care environments, decision-making is usually high-stress, high-stakes and time-sensitive. Decisions on admitting patients to the intensive care unit (ICU) at referral are particularly difficult, as practitioners strive to balance a high demand against a restricted resource.^[5] Analysing and understanding the decision-making process may help to make such daunting decisions more manageable, appropriate and fair. It would also allow for more effective reflection that is essential for attempts to improve such processes.

Novel approaches may better elucidate the complexities of the decision-making process compared with traditional methods. We

have previously used a modified 20-questions game approach to better explore this complex process.^[6] Twenty-questions is a spoken game in which a player chooses an 'object' that others need to guess through a series of strategic questions and the game is won if a correct guess is made within 20 questions.^[7] The rationale for using the game centred around: (i) the game's ability to promote deductive reasoning while limiting information acquired to only that considered vital as per Ashby's law;^[8] and (ii) the game's propensity to allow the clinical case to be reframed from the perspective of the receiver (critical care practitioner) rather than the sender (referring doctor).^[9]

Decision science as applied to medicine has focussed primarily on clinical decision-making, with emphases on diagnostic and management decisions. In practice, however, a series of decisions in other domains, including system-related decisions, are also key in ensuring appropriate

patient care. Operational research methods may be considered in these situations. Operational research is a scientific approach using advanced analytics to the solution of problems in managing complex systems that often involve considerable uncertainty.^[10] Problems are initially broken down into basic components and then solved in defined steps by mathematical analytical methods that include logic, simulation, network analysis (NA),^[11] queueing theory^[12] and game theory.^[13] To explore ICU admission decision-making holistically, a combination of traditional models and operations research may be necessary.

The ICU admission decision process is complex, with numerous non-linear relationships between multiple factors. Identifying and analysing this process warrants the exploration of novel techniques to better describe such inter-relationships. One means of doing this is via NA.^[11] This analysis is based on graph theory^[14] and attempts to identify patterns of connections within a network. NA has been used for social and semantic networks in numerous contexts such as aviation,^[15] social and friendship networks,^[16] linguistics,^[17] doctor networks in health systems,^[18] genome analysis,^[19] and risk identification in healthcare.^[20]

There has been limited use of NA in critical care environments. It has been used to depict information use patterns among ICU nurses,^[21] describe patterns and methods of communication during patient handoffs,^[22] and explore research topics and trends in nursing-related communication in ICU.^[23] NA use has been even more limited in ICU decision-making. It has been used to explore implementation of evidence-informed decision-making interventions,^[24] evaluate decision-making under risk using functional MRI,^[25] and identify nursing diagnosis patterns in ICU.^[26]

Application of a NA model to ICU decision-making may help in identifying key factors that contribute to the decision to admit or refuse a patient referred to ICU. The inter-relationships among factors may be described with emerging patterns better elucidating the complexities of these decision-making processes and describing how doctors work through these processes.

We aimed to identify patterns of ICU decision-making using NA on decision-making process data generated by a 20-questions game approach so as to identify key factors, their distribution, connection and relative importance. The secondary aim was to compare subgroups as per decision outcomes and case prognoses.

Methods

Dataset

The present study was a secondary analysis of a dataset created from a previous study (20-questions study) where the methods were fully described.^[6] Twenty-nine critical care practitioners affiliated to the Discipline of Critical Care at the University of KwaZulu-Natal and responsible for ICU admission and triage decisions were telephonically interviewed to make admission decisions on two hypothetical ICU case referrals created as generic representations for general ICU outcome prognostication. SP posed as the referring doctor for all participants while PDG acted as administrator and tracked the questions. The cases were designed with one (case A) with a poorer prognosis and thus aimed at more likely refusal into ICU, and the other (case B) with a better prognosis and thus aimed at more likely acceptance into ICU. Participants were told that they were being called for an ICU referral with no further patient information volunteered. Participants then posed a series of up to 20 questions seeking specific data to allow them to accumulate information to make a decision on whether the patient should be accepted or refused into the ICU. Each question posed was answered as fully as possible. The participant was able to make an admission decision at any point in the

interview. All interviews were voice recorded. The process was repeated for each of the two cases during the same telephone call.

The recorded interviews were analysed and coded independently by PDG and SP. During case interviews, the following were recorded: case allocation (A or B); each query; number of queries; each question posed; number of questions; and decision made (accept or refuse). A question, defined as an enquiry on a specific factor or aspect of a factor, was counted for 20 questions. A query was defined as any enquiry expressing doubt or requesting further information to establish the validity or accuracy of a question or factor. This may have been an elaboration to add more detail concerning what had already been said or a clarification attempting to make a statement more comprehensible. All coded queries and questions were used for this analysis.

Network analysis

Analysis was conducted using Gephi version 0.9.2 (www.gephi.org; Gephi, France), an open-source, multi-platform network analysis and visualisation software package.^[27] Gephi graphical interface makes it relatively easy to use and allows for broad access to, and exploration of, networks via a real-time graphics rendering process, giving it advantages over other NA software.^[28]

Pre-processing

Data from a previous study^[6] were standardised for this analysis. Every enquiry (query or question) was included. Forty-two clarifications from the previous analysis were recoded as per the query to which they referred. The queries posed were coded into the primary groups of patient-related, physician-related and environment-related (Table 1). Patient-related factors were subcoded into the following secondary groups: acute illness, patient health background and patient profile (PP). These were further classified into tertiary and quaternary groups. The final coding for each query is also recorded in Table 1. All coded queries from the 58 case decisions by 29 practitioners were utilised. A total of 965 queries involved in decision-making were considered as nodes. Duplicates were removed. The movement from one query to the next was considered as an edge.

Modelling assumptions

Various assumptions were made during modelling. Networks may be directed or undirected.^[29] A directed graph contains an ordered pair of nodes and there is a direction associated with the edges that connect the nodes. Undirected graphs have disordered nodes and no direction associated with edges. We opted to use directed graphs as the queries posed in the 20-questions game were considered to be sequential to the order of the participants' questioning. However, this may not necessarily be true in terms of how questions get processed in the minds of the participants and may be more seemingly undirected. We did not consider each individual's networks separately but rather as a composite of all. We did not create an edge from each individual's last node to the first node of the subsequent participant as we considered these to be unconnected. There was also no edge from the last node of a participant's first case and the first node of their second case. It may be argued that these could well have been connected, as the participant's first decision may impact on the second case. However, as we had a break between the cases during the interviews, we felt it better to consider them separately.

We applied specific conditions on the Gephi programme.^[27] Time representations were intervals with self-loops allowed. Parallel edges were not merged. Statistical analysis was used to determine the following measures: degree centrality, harmonic closeness centrality,

betweenness centrality, in-degree prestige, hyperlink-induced topic search (HITS) for authority and hubs, modularity (with a resolution of 0.5) and clustering coefficient.

Measuring centralities

We used three centrality indices to identify the relative importance of individual nodes in the network: degree centrality (number of edges connected to a node); betweenness centrality (number of times a node is present in the shortest path between two other nodes); and closeness centrality (average length of the shortest path from the node to all other nodes).^[30] A higher degree centrality reflects greater shared links with other nodes.^[31] Betweenness centrality indicates that an important node lies on the paths between two other nodes and is a good representation of its influence in the network.^[32] Nodes lying most frequently on these shortest paths have a higher betweenness centrality score. Nodes with the shortest distances to all other nodes will generate a high closeness centrality score. Harmonic centrality is a variant of closeness centrality that deals with infinite values. Rather than summing the distances of a node to all other nodes, the harmonic centrality algorithm sums the inverse of those distances.^[33] All centrality indices identify the most important nodes in the network.

Prestige

Prestige is an alternative means of evaluating the importance of a node by assessing the importance of neighbouring nodes. In a directed graph,

in-degree prestige estimates the importance of a node by the number of edges coming into the node.^[30] A higher in-degree prestige value indicates greater importance.

Hyperlink-induced topic search

The HITS function in Gephi analysis generates two measures, the authority of a node and hub.^[27] The authority of a node is a measure of the value of information stored at that node. A higher authority value indicates a greater value of information. Hub measures the quality of the node's links by estimating the value of the links outgoing from the node.^[34] A higher hub value indicates a greater quality of the node's links.

Modularity

Modularity allows for subgroups of nodes to emerge by applying a community detection algorithm in NA.^[35] The cohesion between the various nodes via the relative density of direct linkages, allows for closely interrelated subgroups or communities to be partitioned.^[31] A good group (i.e. nodes strongly connected) has a higher density of edges within groups than between groups.^[33]

Clustering coefficient

The clustering coefficient measures the degree to which nodes in a graph tend to cluster together. Two versions exist: global and local. The global measure gives an overall indication of clustering in the network. The local measure gives an indication of the embeddedness of each node.^[36]

Table 1. Multi-level coding categories of all queries

First-level code	Second-level code	Third-level code	Fourth-level code	Final coding
Patient	Acute illness	Referral reason (monitoring/support)		Reason
		Diagnosis		AI diagnosis
		Severity		AI severity
		Clinical/physiological parameters		AI CPP
		AI – progress	Timing	AI progress timing
			Intervention	AI progress intervention
			Response to intervention	AI progress response
			Complications	AI progress complications
	Patient health background	Comorbidities	Presence	CM presence
			Severity	CM severity
			Treatment	CM treatment
			Control	CM control
		Fxnal status		Fxnal status
		Nutritional status		Nutritional status
	Personal profile	Age		PP age
		Sex		PP sex
		Name		PP name
		Weight		PP weight
		Wishes		PP wishes
		Health behaviour		PP health behaviour
		Religion		PP religion
		Family		PP family
		Quality of life		QoL
		Other		PP other
Physician	Profile			Physician profile
	Prognosis opinion			PP prognosis opinion
Env	Referral site			Env referral site
	Referring discipline			Env referring discipline
	Resources			Env resources

AI = acute illness; CM = comorbidities; CPP = clinical/physiological parameters; Env = environmental; Fxnal = functional; PP = personal profile; QoL = quality of life.

Subgroup analysis

We subjected the predetermined subgroups to NA to identify differences between them. We compared measures between admit and refuse decision outcomes and between the different prognoses of case A and B.

Ethical considerations

Ethical approval of the original study was granted by the Biomedical Research Ethics Committee at the University of KwaZulu-Natal (ref. no. BE 337/18).^[6] The data were extracted with all identifying information removed. The dataset used in the study contains no personal identifiers of participants.

Results

In total, 965 queries were posed by 29 participants across 58 patient cases resulting in a mean (standard deviation (SD)) of 16.64 (6.96) queries per case. A total of 31 nodes and 964 edges were generated from the coding process.

Node and label size were as per authority measures and nodes were partitioned as per modularity class into different colours in all graphs.

NA measures for all nodes and edges of all patient cases considered together are reflected in Table 2. The modularity measure allowed six subgroups to emerge. Graphical representation of the nodes and edges is shown in Fig. 1. Network analyses of predetermined subgroups for admit v. refuse are reflected in Table 3 and Fig. 2 and for case A v. case B in Table 4 and Fig. 3, respectively.

The 10 most important nodes that emerged when ranked against each NA measure for all cases combined are summarised in Table 5 and the 10 most important nodes from each analysis of the subgroups (admit v. refuse and case A v. case B) when ranked by authority are shown in Table 6. The admit and refuse nodes were excluded from the rankings as they were seen as final decision outcomes (Tables 5 and 6).

Discussion

To our knowledge, this is the first study to use NA to explore ICU admission decisions to identify key factors, their distribution, connection and relative importance. We were only able to do this as a result of data generated from a previous study that used the 20-questions game.^[6]

Assumptions are mandatory for modelling. We chose to use directed graphs as queries in the 20-questions game were thought to be sequential

Table 2. Network analysis measures with all nodes and edges of all cases considered together (N=58)

Label	In-degree prestige (normalised)	Degree	Harmonic closeness centrality	Betweenness centrality	Authority	Hub	Modularity class	Clustering coefficient
AI CPP	0.5	372	0.816667	186.632406	0.594542	0.409526	2	0.936245
AI severity	0.5	242	0.727778	85.260455	0.417022	0.545302	2	0.892391
AI progress intervention	0.466667	150	0.616667	42.51079	0.329318	0.37545	2	0.908945
CM presence	0.4	132	0.761111	45.007874	0.296205	0.189908	1	0.778509
AI diagnosis	0.533333	180	0.761111	133.007741	0.241587	0.400999	0	0.788936
AI progress response	0.333333	88	0.672222	4.539767	0.218561	0.175136	3	0.931035
AI progress timing	0.466667	92	0.683333	20.382552	0.214567	0.206593	0	0.885311
ADMIT	0.466667	40	0	0	0.177882	0	3	0.852564
CM severity	0.333333	138	0.694444	54.87034	0.142015	0.195165	1	0.880119
Fxnal status	0.333333	58	0.688889	43.851511	0.135268	0.091799	1	0.801394
Refuse	0.266667	18	0	0	0.106203	0	2	0.928105
Reason	0.233333	56	0.616667	2.089027	0.103563	0.169565	0	0.866434
CM treatment	0.266667	74	0.633333	14.362096	0.098455	0.083983	1	0.916078
Env - referral site	0.266667	42	0.711111	78.052397	0.093556	0.100721	5	0.648841
PP - age	0.366667	67	0.655556	136.336971	0.079039	0.128519	4	0.488389
CM control	0.1	42	0.594444	1.267657	0.04847	0.059315	1	0.975369
PP - sex	0.066667	45	0.566667	14.388033	0.045887	0.082918	4	0.708245
Nutritional status	0.166667	16	0.544444	0.084989	0.032096	0.030286	1	0.933333
PP - wishes	0.133333	12	0.494444	27	0.030344	0.029835	2	0.833333
PP - religion	0.066667	4	0.477778	0	0.016197	0.015672	2	1
Env - referring discipline	0.133333	8	0.502778	0.126065	0.01587	0.013177	0	0.857143
Phy - prognosis opinion	0.066667	10	0.380556	0.613671	0.013749	0.003137	3	0.8
Phy - profile	0.066667	6	0.491667	0.076923	0.010219	0.013324	5	1
Env - resources	0.066667	4	0.422222	0	0.008656	0.004358	5	1
PP - health behaviour	0.133333	12	0.527778	28.221657	0.007023	0.042314	1	0.787879
QoL	0.033333	2	0.416667	0	0.006802	0.002295	0	1
AI progress complications	0.033333	2	0.416667	0.005525	0.006369	0.002409	1	1
PP - name	0.1	8	0.433333	29.050914	0.00389	0.006141	4	0.428571
PP - weight	0.033333	2	0.461111	0	0.00218	0.010085	4	1
PP - other	0.033333	2	0.318889	0	0.001709	0.000066	5	1
PP - family	0.033333	4	0.425	0.260639	0.000506	0.001587	5	0

AI = acute illness; CM = comorbidities; CPP = clinical/physiological parameters; Env = environmental; Fxnal = functional; Phy = physician; PP = personal profile; QoL = quality of life. Nodes are ranked as per authority measure.

as part of the participants' deductive reasoning. Questioning during referrals often appears to be directed even though the thought process may be more complex. An argument may thus be made for undirected networks. This was verified by separately running the analysis for all cases as an undirected network and similar factors emerged as the most important. The absence of an edge from the last node of a participant's first case and the first node of the second case, may also be questioned as one decision-making process, invariably affecting the subsequent node.^[37,38] We, however, considered it better to view the cases separately as we had attempted to create a clear break between the cases during the interviews in the 20-questions study.^[6]

We sought to describe two main issues: (i) the relative importance of the nodes (emergent factors); and (ii) their relationship/connection with each other. The best measures to evaluate these two issues remain controversial. As no single measure may be considered ideal to establish the relative importance of nodes, we ran the analysis using measures of centrality, prestige, authority and hubs. Regardless of the measure used, properties of the acute illness (diagnosis, severity, and clinical and

physiological parameters (CPP)), progress of the acute illness (intervention/response/timing) and properties of comorbidities (presence and severity) appeared consistently. However, the relative rankings of these factors differed. In addition, functional status and patient age variably emerged in four of the six measures. It was unsurprising that patients' functional status (defined by activities of daily living) emerged as important, as it has been previously found to impact admission decisions in traditional studies in the field describing frequencies.^[39-41] The emergence of age as an important factor is controversial. A recent review was inconclusive, with some studies contradicting others that found patient age to be significant, with the suggestion that physiological age or an assessment of frailty, may be more important than chronological age.^[42] The referral site emerged as an important factor when harmonic closeness centrality and betweenness centrality was used. The reason for admission emerged only when authority and hub were used. The patient name emerged as important only when betweenness centrality was used. This may have emerged as an important node, as it is often sought by receiving practitioners for administrative purposes and is often asked out of habit. Overall, using various measures identified different factors as important,

The 10 most common factors emerging from the previously conducted frequency analysis study^[6] are also reflected in Table 5. Differences are noted with each NA measure in terms of the emergent factors (nodes) and their relative rankings. Of the six measures used, the hub list most closely resembles the frequency list, with the same 10 nodes emerging with a minor change in their relative ranking. It may thus be recommended that in analyses such as these, multiple measures of node importance must be utilised.

Modularity was used to describe relationships among nodes with six communities emerging (Table 2). The communities bear little resemblance to the various groups of codes in Table 1. The implication of this is that the nodes within a community are more tightly connected to each other than with nodes outside the community. The PP factors are widely distributed among the communities, with patient's age, sex, weight and name in Community 4 and patient wishes and religion in Community 2. This may suggest that the way factors (nodes) have been traditionally subgrouped (Table 1) may need to be reconsidered, with different subgroups/communities being partitioned to better reflect the connection of these nodes in the thought processes of decision makers rather than in classic algorithms.

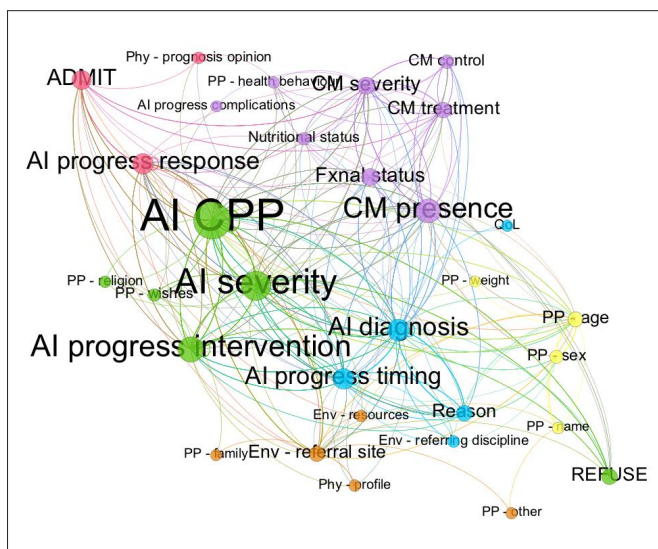


Fig. 1. Network analysis graph of all cases. Node size and label size are as per authority measures and nodes are partitioned as per modularity class into different colours.

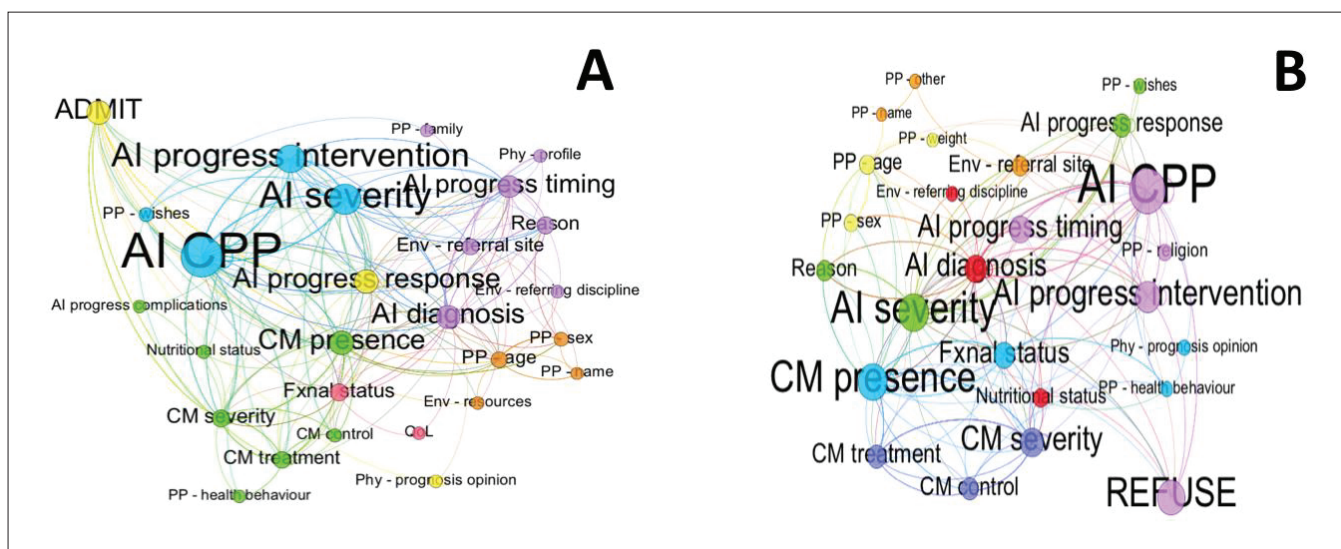


Fig. 2. Network analysis graph of admitted cases (A) and refused cases (B). Node size and label size are as per authority measures and nodes are partitioned as per modularity class into different colours.

Table 3. Network analysis measures as per decision outcomes (admit v. refuse)

Label*	In-degree prestige (normalised)				Degree				Harmonic closeness centrality				Betweenness centrality				Authority				Hub				Modularity class				Clustering coefficient			
	A		R		A		R		A		R		A		R		A		R		A		R		A		R		A		R	
	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R		
Admit	0.538462	Nil [†]	40	Nil	0	Nil	0	Nil	0	Nil	0	Nil	0	245314	Nil	0	Nil	0	Nil	0	Nil	0	Nil	2	Nil	0	765385	Nil				
AI CPP	0.423077	0.583333	232	140	0.784722	0.784722	94.297657	175.610075	0.621456	0.500644	0.375821	0.477177	1	4	0.916855	0.871519																
AI diagnosis	0.576923	0.541667	116	64	0.762821	0.708333	131.872046	70.291592	0.244389	0.221194	0.383927	0.377893	0	6	0.696203	0.674797																
AI progress complications	0.038462	Nil	2	Nil	0.413462	Nil	0.018727	Nil	0.008989	Nil	0.002546	Nil	5	Nil	1	Nil																
AI progress intervention	0.423077	0.375	104	46	0.628205	0.586806	34.525737	6.711946	0.34099	0.27734	0.378096	0.336052	1	4	0.883131	0.821505																
AI progress response	0.384615	0.208333	68	20	0.705128	0.510417	9.04915	0.137931	0.241391	0.142038	0.183218	0.136079	2	0	0.874396	1																
AI progress timing	0.5	0.208333	70	22	0.692308	0.565972	30.470101	0.309523	0.206785	0.209269	0.184049	0.193749	0	4	0.810628	1																
AI severity	0.461538	0.541667	168	74	0.679487	0.729167	65.164947	96.929861	0.402807	0.378867	0.603438	0.438177	1	0	0.897081	0.721633																
CM control	0.115385	0.125	18	24	0.548077	0.579861	0.90583	2.649424	0.020871	0.128262	0.040215	0.117441	5	5	0.835165	0.904412																
CM presence	0.384615	0.458333	76	56	0.75	0.663194	48.394118	58.310553	0.244269	0.367035	0.172685	0.255492	5	3	0.705051	0.68525																
CM severity	0.269231	0.333333	84	54	0.673077	0.697917	51.094576	25.565285	0.107071	0.239138	0.180273	0.250744	5	5	0.87594	0.758258																
CM treatment	0.269231	0.208333	42	32	0.621795	0.600694	27.117445	3.766195	0.084836	0.141723	0.057308	0.170606	5	5	0.827586	0.924901																
Env - referral site	0.269231	0.166667	28	14	0.653846	0.604167	48.794068	44.420346	0.082534	0.099203	0.095596	0.109756	0	1	0.623333	0.722222																
Env - referring discipline	0.115385	0.041667	6	2	0.503205	0.427083	0.28209	0	0.008226	0.023109	0.012489	0.011665	0	6	0.8	1																
Env - resources	0.076923	Nil	4	Nil	0.419872	Nil	0	Nil	0.011208	Nil	0.007595	Nil	3	Nil	1	Nil																
Fxnal status	0.307692	0.25	34	24	0.660256	0.628472	28.333386	16.032496	0.105476	0.188317	0.076197	0.150901	4	3	0.74	0.71345																
Nutritional status	0.076923	0.166667	4	12	0.467949	0.538194	0	0.179537	0.013041	0.0795	0.012122	0.080737	5	6	0.833333	0.866667																
Phy - profile	0.076923	Nil	6	Nil	0.496795	Nil	0.371882	Nil	0.013674	Nil	0.018834	Nil	0	Nil	0.7	Nil																
Phy - prognosis opinion	0.038462	0.041667	6	4	1	0.355556	0.005319	3.880679	0.009128	0.025165	0.005832	0.001169	2	3	0.666667	1																
PP - age	0.346154	0.25	43	24	0.634615	0.652778	75.251302	90.020701	0.074123	0.087073	0.116021	0.149634	3	2	0.463458	0.442105																
PP - family	0.038462	Nil	4	Nil	0.407051	Nil	0.484013	Nil	0.000787	Nil	0.001962	Nil	0	Nil	0	Nil																
PP - health behaviour	0.038462	0.125	4	8	0.467949	0.510417	0.05	23.910714	0.002725	0.022172	0.012122	0.087413	5	3	0.5	0.607143																
PP - name	0.076923	0.041667	6	2	0.432692	0.413194	0.1483	23	0.005031	0	0.006209	0.004592	3	1	0.6	0																
PP - other	Nil	0.041667	Nil	2	Nil	0.317361	Nil	22	Nil	0.005788	Nil	0	Nil	1	Nil	0																
PP - religion	Nil	0.083333	Nil	4	Nil	0.46875	Nil	0	Nil	0.048274	Nil	0.041029	Nil	4	Nil	1																
PP - sex	0.076923	0.041667	30	15	0.564103	0.53125	10.661363	1.193871	0.038766	0.05524	0.066345	0.10323	3	2	0.514943	0.769231																
PP - weight	Nil	0.041667	Nil	2	Nil	0.454861	Nil	0	Nil	0.007891	Nil	0.026403	Nil	2	Nil	1																
PP - wishes	0.153846	0.041667	10	2	0.490385	0.434028	23.029197	0	0.030619	0.025165	0.033112	0.019981	1	0	0.755556	1																
QoL	0.038462	Nil	2	Nil	0.410256	Nil	0	Nil	0.009128	Nil	0.002508	Nil	4	Nil	1	Nil																
Reason	0.230769	0.125	41	15	0.583333	0.545139	2.678746	3.079272	0.094145	0.105655	0.186407	0.111814	0	0	0.862366	0.939394																
Refuse	Nil	0.333333	Nil	18	Nil	0	Nil	0	Nil	0.330795	Nil	0	Nil	4	Nil	0.875817																

A = admit; R= refuse; AI = acute illness; CM = comorbidities; CPP = clinical/physiological parameters; Env = environmental; Fxnal = functional; Phy = physician; PP = personal profile; QoL = quality of life.

*Nodes listed alphabetically.

[†]Cells with 'Nil' indicate absence of the node in the respective network.

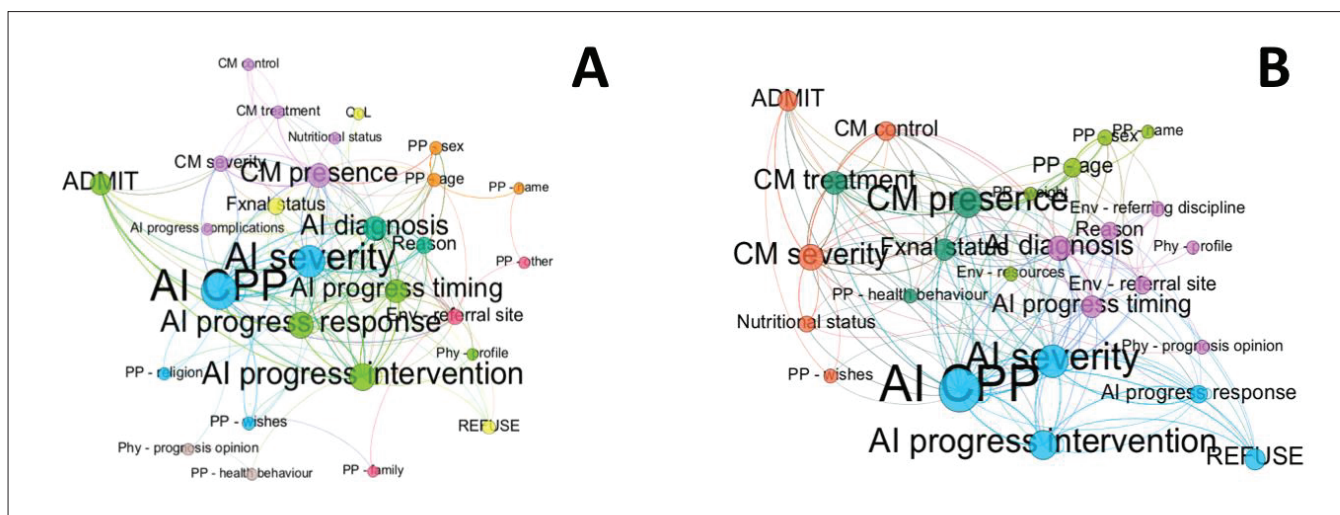


Fig. 3. Network analysis graph of case A (A) and case B (B).

The secondary aim was to compare subgroups as per decision outcomes (admit v. refuse) and case labels (case A v. case B) (Table 6). The admit and refuse subgroups were largely similar in respect of the 10 most important nodes ranked by authority, with only the reason for admission being replaced by comorbidity treatment. The relative rankings of the nodes were considered to be only slightly different. In the complete list of nodes for each subgroup, 5 nodes (AI progress complications, env resources, physician profile, PP family, QoL) appeared exclusively in the admit subgroup, while PP other, PP religion, PP weight were exclusively in the refuse subgroup (Table 3). The admit subgroup was partitioned into 6 communities and the refuse subgroup into 7 communities, with nodes differentially associated. The significance of the above differences, while not totally clear, may suggest that the thought processes for the two decision outcomes may be different. In the 20-questions study analysis, a longer time taken for refusals was noted, with no significant differences in the number of queries and questions.^[6]

Three of the 10 most important nodes (ranked by authority) were entirely different between case A and case B by comparing NA (Table 6). Three nodes (env referring discipline, env resources, PP weight) appeared exclusively in the case A subgroup while 5 (AI progress complications, PP family, PP other, PP religion, QoL) appeared exclusively in the case B subgroup in the complete list of nodes (Table 4). Case A subgroup was partitioned into 5 communities and the case B subgroup was partitioned into 8 communities with nodes differentially associated. In contrast, no significant differences were found between the subgroups in the 20-questions study.^[6]

Study limitations

The main limitation of this study was the relatively small dataset of 965 queries. However, as such an analysis has not been previously conducted in this context, we opted to use the available data for analysis. Further, we used data that were extracted from a previous study.^[6] The novel use of the 20-questions game approach^[6] as a method to collect data has not been validated. Such an artificial construct may be different from the clinical setting, where a large amount of standardised information would be routinely provided. The assumption that the decision-making process will be similar in both circumstances may thus be questioned. Additionally, the assumption that questions were posed sequentially may also be questioned, as thought processes involved in decision-making may not necessarily follow sequentially. Nevertheless, we opted

to test if the comparison could potentially reveal insights into the decision-making process, accepting that any results would need to be interpreted with caution.

An additional limitation of this study is the generalisability of the results as the extracted data were limited to one local group of practitioners, whose admission decision thought processes may be contextual. Assumptions needed to allow for modelling may also act as limitations. Furthermore, the analysis was subject to the algorithms of the Gephi software.^[27] Different software packages may have variations in how some of the analyses are conducted.

Finally, although the results of the study yield important information regarding patient data required for admission decision-making, it is important to note that this is only one aspect of a complex admission decision-making process. Other aspects contributing to the admission decision-making process should be explored using non-traditional research approaches.

Conclusion

To better describe and analyse the complex ICU admission decision process, exploration of novel techniques is warranted so that the importance and interrelationships of contributory factors are more clearly delineated. The use of network analysis with its various measures has facilitated a more comprehensive exploration of the ICU admission decision, allowing us to reflect on this often difficult, high-stakes, high-stress and time-sensitive process. Further studies with larger datasets are needed to better elucidate the exact role of network analysis in decision-making processes.

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Table 4. Network analysis measures as per case labels (case A v. case B)

Label	In-degree prestige (normalised)		Degree		Harmonic closeness centrality		Betweenness centrality		Authority		Hub		Clustering coefficient		Clustering coefficient	
	Case A	Case B	Case A	Case B	Case A	Case B	Case A	Case B	Case A	Case B	Case A	Case B	Case A	Case B	Case A	Case B
Admit	0.36	0.37037	16	24	0	0	0	0	0.147263	0.21991	0	0	4	4	0.741667	0.782609
AI CPP	0.56	0.407407	210	162	0.793333	0.765432	118.231819	143.448075	0.580744	0.54457	0.444964	0.444964	3	3	0.893968	0.907895
AI diagnosis	0.6	0.407407	96	84	0.78	0.703704	120.116662	82.947346	0.215979	0.269759	0.409564	0.409564	0	0	0.704659	0.755416
AI progress complications	Nil	0.037037	Nil	2	Nil	0.383951	Nil	0.096195	Nil	0.013597	Nil	0.013597	Nil	5	Nil	1
AI progress intervention	0.28	0.518519	58	92	0.58	0.632716	1.408138	109.860956	0.307158	0.33154	0.292323	0.292323	3	4	0.950089	0.813559
AI progress response	0.24	0.333333	30	58	0.573333	0.648148	0.457246	14.91625	0.096686	0.309761	0.103805	0.103805	3	4	0.964912	0.85641
AI progress timing	0.36	0.37037	38	54	0.653333	0.608025	8.168304	20.903587	0.170652	0.250541	0.18944	0.18944	0	4	0.862319	0.885886
AI severity	0.52	0.37037	110	132	0.76	0.703704	69.197159	85.321802	0.382593	0.441059	0.509566	0.509566	3	3	0.810663	0.890419
CM control	0.12	0.074074	36	6	0.626667	0.408642	1.725243	1	0.119246	0.006755	0.123217	0.123217	4	5	0.975385	1
CM presence	0.48	0.333333	70	62	0.713333	0.700617	33.048972	92.416812	0.328592	0.258399	0.244468	0.244468	1	5	0.766597	0.600465
CM severity	0.36	0.185185	80	58	0.713333	0.595679	26.615642	49.756544	0.251473	0.085444	0.246635	0.246635	4	5	0.777979	0.866366
CM treatment	0.32	0.111111	58	16	0.646667	0.537037	16.024925	5.893194	0.205595	0.021788	0.185015	0.185015	1	5	0.884146	0.836364
Env - referral site	0.12	0.296296	16	26	0.586667	0.648148	30.116171	80.687428	0.081455	0.09977	0.074102	0.074102	0	7	0.641026	0.645022
Env - referring discipline	0.16	Nil	8	Nil	0.526667	Nil	0.687012	Nil	0.028853	Nil	0.024101	0.024101	0	Nil	0.809524	Nil
Env - resources	0.08	Nil	4	Nil	0.44	Nil	0.209524	Nil	0.017633	Nil	0.008633	0.008633	2	Nil	0.833333	Nil
Fxnal status	0.28	0.259259	34	24	0.626667	0.641975	9.50391	33.279651	0.163092	0.109512	0.125438	0.125438	1	1	0.843333	0.654971
Nutritional status	0.16	0.037037	14	2	0.54	0.42284	0.129681	0	0.065161	0.005594	0.05815	0.05815	4	5	0.892857	1
Phy - profile	0.04	0.074074	2	4	0.453333	0.438272	0.12936	0	0.002517	0.015469	0.007337	0.007337	0	4	1	1
Phy - prognosis opinion	0.04	0.037037	6	4	1	0.306173	0.038462	24	0.013913	0.012526	0.005002	0.005002	0	6	0.666667	0
PP - age	0.36	0.259259	38	29	0.68	0.604938	94.549419	74.73911	0.106891	0.051002	0.150093	0.150093	2	2	0.550538	0.276667
PP - family	Nil	0.037037	Nil	4	Nil	0.404321	Nil	0.665446	Nil	0.00124	Nil	0.00124	Nil	7	Nil	0
PP - health behaviour	0.12	0.037037	10	2	0.52	0.399383	0.285011	26	0.025278	0	0.07399	0.07399	1	6	0.955556	0
PP - name	0.08	0.037037	5	3	0.453333	0.391975	1.291738	26	0.007616	0	0.008831	0.008831	2	2	0.666667	0
PP - other	Nil	0.037037	Nil	2	Nil	0.303086	Nil	24	Nil	0.003647	Nil	0.003647	Nil	7	Nil	0
PP - religion	Nil	0.074074	Nil	4	Nil	0.462963	Nil	0	Nil	0.02955	Nil	0.02955	Nil	3	Nil	1
PP - sex	0.08	0.037037	21	24	0.593333	0.493827	8.200351	2.618182	0.046187	0.038974	0.076284	0.076284	2	2	0.689474	0.666667
PP - weight	0.04	Nil	2	Nil	0.456667	Nil	0	Nil	0.005099	Nil	0.019728	0.019728	2	Nil	1	Nil
PP - wishes	0.08	0.111111	4	8	0.466667	0.475309	0	24	0.023493	0.038355	0.017999	0.017999	4	3	1	0.75
QoL	Nil	0.037037	Nil	2	Nil	0.401235	Nil	0	Nil	0.011823	Nil	0.011823	Nil	1	Nil	1
Reason	0.16	0.222222	21	35	0.626667	0.583333	0.865254	5.449424	0.089591	0.113911	0.111938	0.111938	0	0	0.895238	0.794872
Refuse	0.28	0.185185	13	5	0	0	0	0	0.160703	0.04892	0	0	3	1	0.897436	0.9

AI = acute illness; CM = comorbidities; CPP = clinical/physiological parameters; Env = environmental; Fxnal = functional; Phy = physician; PP = personal profile; QoL = quality of life. Nodes listed alphabetically. Cells with 'Nil' indicate absence of the node in the respective network.

Table 5. Top 10 ranking nodes from network analysis comparing each measure*

In-degree prestige		Harmonic closeness		Betweenness centrality		Authority		Hub		Frequency ^{†6††}	
Rank	(normalised)	Rank	Degree	Rank	centrality	Rank	centrality	Rank	Hub	Rank	Frequency ^{†6††}
1	AI diagnosis	1	AI CPP	1	AI CPP	1	AI CPP	1	AI severity	1	AI CPP
2	AI severity	2	AI severity	2	AI diagnosis	2	PP - age	2	AI CPP	2	AI severity
2	AI CPP	3	AI diagnosis	2	CM presence	3	AI diagnosis	3	AI progress intervention	3	AI diagnosis
4	AI progress intervention	4	AI progress intervention	4	AI severity	4	AI severity	4	CM presence	4	AI progress intervention
4	AI progress timing	5	CM severity	5	Env - referral site	5	Env - referral site	5	AI diagnosis	5	CM presence
6	CM presence	6	CM presence	6	CM severity	6	CM severity	6	AI progress response	6	PP - age
7	PP - age	7	AI progress timing	7	Fxnal status	7	CM presence	7	AI progress timing	7	CM severity
8	CM severity	8	AI progress response	8	AI progress timing	8	Fxnal status	8	CM severity	8	AI progress timing
8	Fxnal status	9	CM treatment	9	AI progress response	9	AI progress intervention	9	Fxnal status	9	AI progress response
8	AI progress response	10	PP - age	10	PP - age	10	PP - name	10	Reason	10	Reason

AI = acute illness; CM = comorbidities; CPP = clinical/physiological parameters; Env = environmental; Fxnal = functional; Phy = physician; PP = personal profile.
 *Admit and refuse nodes were excluded from the rankings.
 †Gopalan *et al.* (2020).

Table 6. Top 10 nodes ranked as per authority comparing subgroups (admits v. refuse and case A v. case B)

Rank	All cases	Decision outcomes		Case labels	
		Admits	Refuse	Case A	Case B
1	AI CPP	AI CPP	AI CPP	AI CPP	AI CPP
2	AI severity	AI severity	AI severity	AI severity	AI severity
3	AI progress intervention	AI progress intervention	CM presence	CM presence	AI progress intervention
4	CM presence	AI diagnosis	AI progress intervention	AI progress intervention	AI progress response
5	AI diagnosis	CM presence	CM severity	CM severity	AI diagnosis
6	AI progress response	AI progress response	AI diagnosis	AI diagnosis	CM presence
7	AI progress timing	AI progress timing	AI progress timing	CM treatment	AI progress timing
8	CM severity	CM severity	Fxnal status	AI progress timing	Reason
9	Fxnal status	Fxnal status	AI progress response	Fxnal status	Fxnal status
10	Reason	Reason	CM treatment	CM control	Env - referral site

AI = acute illness; CM = comorbidities; CPP = clinical/physiological parameters; Env = environmental; Fxnal = functional.

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