

# Exploratory Network Analysis of Clinical Interactions in the ED

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<sup>a</sup>Repository ([https://github.com/tommyflynn/Flynn\\_N741\\_Project/tree/master/Flynn\\_Project](https://github.com/tommyflynn/Flynn_N741_Project/tree/master/Flynn_Project))

## Abstract

Patient acuity in the Emergency Department is triaged at the beginning of the care process using the Emergency Severity Index (ESI) metric. The ESI is presumed to predict resource consumption in the ED, and is a validated predictor of hospital admission for the majority of ED patients. It is not sensitive to non-medical patient characteristics, such as patient race, nor is it accountable to changes in patient condition over time. ED administrators and charge nurses are left with an impression of the unit that does not reveal the reality of current patient conditions or ED resources being utilized. The lack of real-time ED resource and patient condition information creates opportunities for unrecognized patient deterioration, medical errors, increased wait times, and decreased patient satisfaction. An objective measurement of patient resource consumption that passively observes and calculates relative patient need in real-time would allow charge nurses and administrators to make informed decisions for effective, efficient, and safe patient care. This study tests a novel approach to measuring patient acuity (ED resource consumption) using real-time location system (RTLS) contact data and network analysis. This paper presents the approach and analytic results of several ED contact networks in relation to patient acuity (ESI)

## Research Question & Specific Aims

- Can network analysis of clinical interactions between patients and staff provide insight into the complex Emergency Department patient care process? (Canto et al. 2000) Aim 1: Explore the network of clinical interactions in the ED between patients and staff to determine whether predictable patterns emerge in terms of centrality, density, and change over time. Aim 2: Test the association between patient acuity and network position measure of eigenvector centrality of patient composite network, compared to the centrality of the dynamic patient network (measure TBD).

## Background & Objectives

Intelligent clinical monitoring software is not a new idea, but advancements in the field of data science continue to yield powerful new tools that may make such software a reality in the near future. (Yu et al. 2015, Donoho (2017)) Real-time location systems (RTLS) are increasingly common in hospitals across the nation, especially in clinical areas where patient care and flow are both complex and time-sensitive, such as the Emergency Department (ED). (Yao, Chu, and Li 2012) A bird's-eye view of a busy urban ED might resemble a hive of frenzied bees, but as we have learned of beehives, patterns of work and interactions within EDs are necessarily purposed and complexly adaptive to the various needs of the system (or hive) as a whole. (Kridi, Carvalho, and Gomes 2016) By leveraging the technology of RTLS and analytical power of network analysis, future ED monitoring systems will provide ED leadership with real-time resource allocation and patient condition information. The Emergency Severity Index (ESI) is a validated metric used to triage patients in US Emergency Departments. (Tanabe et al. 2004) That triage nurse may decide to involve the charge nurse or a physician given various concerns about the patient. These interactions, observed and measured by the Real Time Location System (RTLS), continue as more

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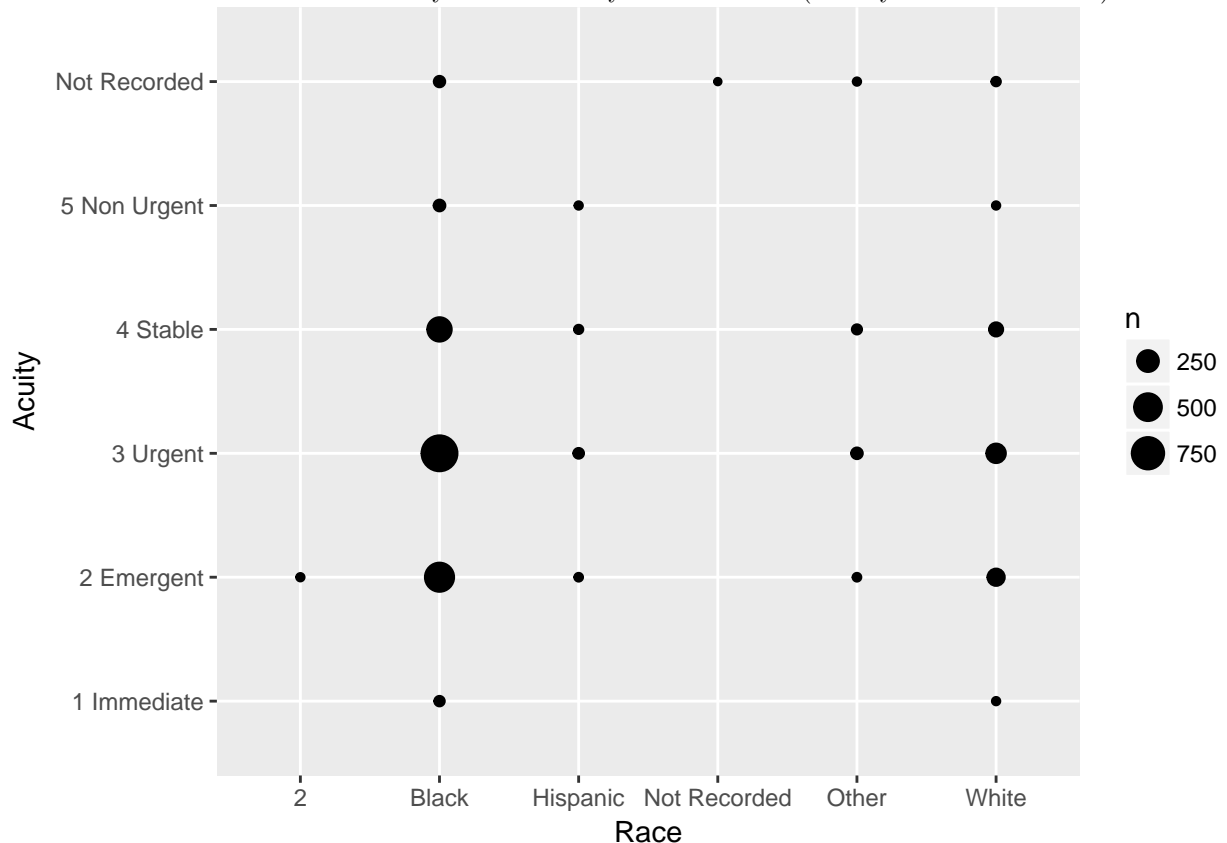
Email address: [tjflynn@emory.edu](mailto:tjflynn@emory.edu) (Tommy Flynn)

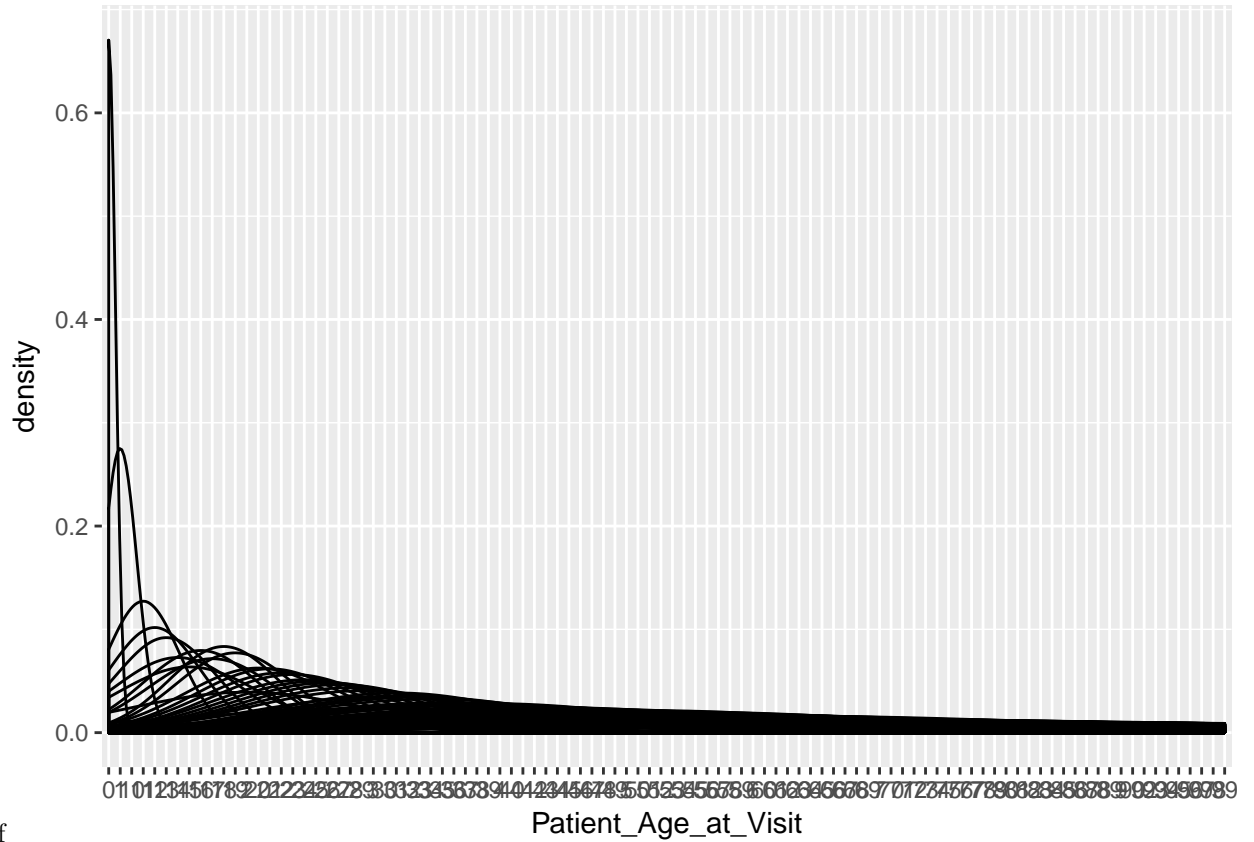
patients are triaged, moved into patient rooms, and so on toward a vast and complex network of interactions. This web of care is likely to correlate with the amount and quality of care delivered to individual patients. - **The purpose of this study is to explore the network of clinical interactions that take place in the Emergency Department and describe the relationship between those network variables and patient acuity.** To study this relationship, received permission to analyse existing data that includes the following; the frequency and duration of all face-to-face interactions (patients, providers, nurses, technicians, & administrators) that occurred in the ED for 81 12hr shifts, the location of those interactions, and individual patients' medical and demographic characteristics including acuity, chief complaint, gender, age, arrival mode, and disposition. The network structural characteristics will be assessed in relation to the industry standard acuity measure, the Emergency Severity Index (ESI), and potential confounding variables. Using this data will require specific knowledge of the R statistical packages, network analysis, and data science. See Tables 1-4 for my learning goals with respective action items, timeline, and outcomes.

## Methods

### RTLS Data

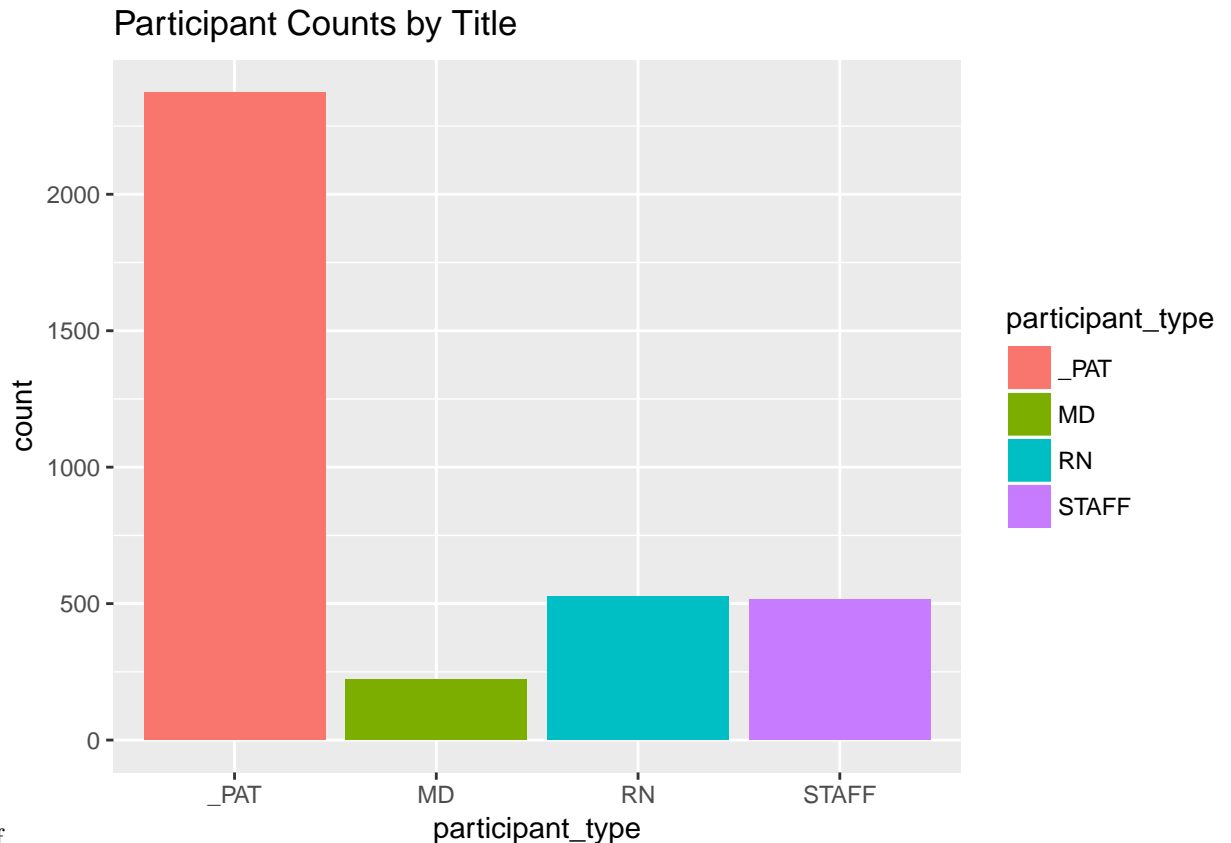
This study applies a secondary data analysis design due to the exploratory nature of the research aims. Data was made available with permissions from the originating research team. The purpose of the original study was to describe contact characteristics between patients and staff in the ED of a busy urban hospital to inform cross-infection control measures. Data were collected using a radio-frequency identification system that triangulated patient and staff (nurses, providers, and ancillary staff) locations within the ED at Emory University Hospital Midtown. Data for this secondary analysis were collected using a prospective, longitudinal, observational design with a random sampling of one day shift and one night shift per week for one year, July 1, 2009 to June 30, 2010. This strategy was chosen to minimize sampling bias related to seasonal or weekly fluctuations in census, acuity, and ED staffing changes. Although a total of 104 shifts were observed, the original research team retained only 81 shifts for reasons related to issues with the RFID system and study staff sick leave. (Lowery-North et al. 2013) datasets-





datasets-2.pdf

## [1] "sid"	"numshift"	"d8"
## [4] "shift_ampm"	"Reason_shortShift"	"startd8time"
## [7] "endd8time"	"shift_d8_ampm"	"quarter"
## [10] "weekday"	"H1N1"	"ED_ARRIVAL"
## [13] "ed_departure"	"durationInED"	"duration_UntilTag"
## [16] "Sex"	"Patient_Age_at_Visit"	"Race"
## [19] "Chief_Complaint"	"Acuity"	"Arr_Mode"
## [22] "ED_Disposition"	"daysinED"	"MinutesInED"
## [25] "AGE"	"ILI_Syndrome"	"ILIwMissing"
## [28] "hrsInED"	"timeCoveredbyShift"	"popnFreqbyshift"
## [31] "shift_num_ampm"	"Participant_final"	



datasets-3.pdf  
#Results

## Analysis Plan

### Data Exploration & Cleaning

Data will be maintained in private repositories in the GitHub version control platform. Patient characteristic data will be evaluated for missing or implausible data with descriptive analyses, and RFID generated networks will be included for statistical analysis if variables of network density, centrality, and a network diversity scale are distributed normally across networks.

Why do I find 1102 unique nodes in the vertices data, 1023 unique nodes in the edges dataset, and 1017 unique patients in the patient characteristics dataset?

Descriptive statistics of the network data as well as patient demographic data will be evaluated for assumptions of normality. The data will be skewed in certain predictable ways due to the observed patient populations. The distribution of study subject demographics will be described in tabular format, noting irregularities and potential sources of error.

*Variables available for final analysis:*

**Network Variables** > - Network Centrality (based on the eigenvector up to, but not including, any other patient-staff interactions) > - Network density > - Network clustering coefficient

**Staff title** > - Title (RN, MD, Other Staff)

**Patient variables** > - *Acuity* (ESI, independent variable of interest) > - Gender > - Age > - Race > - Arrival mode (ambulance v. walk-in) > - Disposition (admission v. discharge) > - Length of stay (common measure of quality in the literature used for comparison)

## Analysis

The open-source R statistical language and R-Studio user interface from the developers at CRAN were used for all data exploration, wrangling, cleaning, description, and analysis.(R Core Team 2017) Pandoc's Markdown allows for seamless integration of code, results, visualizations, and author interpretation of the research into a single document.(Allaire et al. 2017) Running all code and calculating all results within the manuscript itself, Markdown eliminates risk for errors in transferring statistical software output into foreign documents. The data were explored, cleaned, and assessed for statistical assumptions using the Tidyverse group of R packages.(Wickham 2017, Wickham (2016)) Data were prepared for network analysis with the iGraph package.(Csardi and Nepusz 2006) Multiple linear regression will be used for the final analysis to assess the correlation between patient acuity and patient centrality. Relationships will be evaluated visually (see below) as well as statistically to an alpha of 0.05.

## Results

Results will be discussed with the visual supplementation of network graphs. This allows the reader to understand concepts that may be difficult to grasp through text alone.

## Discussion

Allocating staff resources in an Emergency Department is an ongoing challenge. How can these results begin to offer solutions to ED staff and patient management?

What were my primary limitation (both expected and unexpected)?

## Conclusion

Did I meet my learning objectives? How would I design a better study next time?

## References

Allaire, JJ, Jeffrey Horner, Vicent Marti, and Natacha Porte. 2017. *Markdown: 'Markdown' Rendering for R*. <https://CRAN.R-project.org/package=markdown>.

Canto, John G., Jeroan J. Allison, Catarina I. Kiefe, Contessa Fincher, Robert Farmer, Padmini Sekar, Sharina Person, and Norman W. Weissman. 2000. "Relation of Race and Sex to the Use of Reperfusion Therapy in Medicare Beneficiaries with Acute Myocardial Infarction." *Journal Article. New England Journal of Medicine* 342 (15): 1094–1100. doi:[10.1056/NEJM200004133421505](https://doi.org/10.1056/NEJM200004133421505).

Csardi, Gabor, and Tamas Nepusz. 2006. "The Igraph Software Package for Complex Network Research." *InterJournal Complex Systems*: 1695. <http://igraph.org>.

Donoho, David. 2017. "50 Years of Data Science." *Journal Article. Journal of Computational and Graphical Statistics* 26 (4): 745–66. doi:[10.1080/10618600.2017.1384734](https://doi.org/10.1080/10618600.2017.1384734).

Kridi, Douglas S., Carlos Giovanni N. de Carvalho, and Danielo G. Gomes. 2016. "Application of Wireless Sensor Networks for Beehive Monitoring and in-Hive Thermal Patterns Detection." *Computers and Electronics in Agriculture* 127: 221–35. doi:<https://doi.org/10.1016/j.compag.2016.05.013>.

Lowery-North, Douglas W., Vicki Stover Hertzberg, Lisa Elon, George Cotsonis, Sarah A. Hilton, II Vaughns Christopher F., Eric Hill, Alok Shrestha, Alexandria Jo, and Nathan Adams. 2013. "Measuring Social Contacts

in the Emergency Department.” Journal Article. *PLoS ONE* 8 (8): e70854. doi:[10.1371/journal.pone.0070854](https://doi.org/10.1371/journal.pone.0070854).

R Core Team. 2017. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.

Tanabe, Paula, Rick Gimbel, Paul R. Yarnold, and James G. Adams. 2004. “The Emergency Severity Index (Version 3) 5-Level Triage System Scores Predict Ed Resource Consumption.” Journal Article. *Journal of Emergency Nursing* 30 (1): 22–29. doi:<http://dx.doi.org/10.1016/j.jen.2003.11.004>.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. <http://ggplot2.org>.

———. 2017. *Tidyverse: Easily Install and Load the 'Tidyverse'*. <https://CRAN.R-project.org/package=tidyverse>.

Yao, Wen, Chao-Hsien Chu, and Zang Li. 2012. “The Adoption and Implementation of Rfid Technologies in Healthcare: A Literature Review.” Journal Article. *Journal of Medical Systems* 36 (6): 3507–25. doi:[10.1007/s10916-011-9789-8](https://doi.org/10.1007/s10916-011-9789-8).

Yu, Denny, Renaldo C. Blocker, Mustafa Y. Sir, M. Susan Hallbeck, Thomas R. Hellmich, Tara Cohen, David M. Nestler, and Kalyan S. Pasupathy. 2015. “Intelligent Emergency Department: Validation of Sociometers to Study Workload.” Journal Article. *Journal of Medical Systems* 40 (3): 53. doi:[10.1007/s10916-015-0405-1](https://doi.org/10.1007/s10916-015-0405-1).