TITLE PAGE

Title: Connected Cancer Care: EHR Communication Networks in Virtual Cancer Care Teams

Principal Investigator: Xi Zhu

Team Members: Dan Sewell, Vimal Mishra, Alan Dow, Khalid Matin, Haomin Li, Eldon Sorensen

Organization: Department of Health Management and Policy, University of Iowa

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Federal Project Officer: Sheena Patel

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1. STRUCTURED ABSTRACT

Purpose: The widespread adoption of EHR is changing how healthcare professionals (HCPs) deliver care and communicate with each other. How EHR transforms team-based care is identified as a high-priority research area by the National Academy of Medicine, Agency for Healthcare Research and Quality (AHRQ), and President's Cancer Panel for generating and applying new evidence to facilitate the effective and efficient collection, flow, and use of health information in care delivery. The objective of this project is to develop methods for measuring EHR communication networks in virtual care teams and examine the relationship between EHR communication networks and care quality.

Scope: Cancer care routinely is delivered by diverse teams of HCPs who engage in complex communication and interactions across care settings. In this study, we will adopt a patient-centric approach to measure information sharing in teams caring for breast, colorectal, and non-small cell lung cancer patients using HCPs' direct access to the same patient's EHR record. The study was conducted using a retrospective patient sample receiving care at the Virginia Commonwealth University (VCU) Massey Cancer Center.

Methods: Data on patient demographics, diagnosis, treatment, comorbidity, mortality, and utilization of inpatient and outpatient services after cancer diagnosis as well as time-stamped HCP access to patient EHR records were extracted. We tested multiple approaches in Social Network Analysis (SNA) for measuring topological structures of the temporal EHR communication networks. We examined the associations between EHR communication network structures and patient outcomes including survival time and ED visits using a causal mediation analysis framework.

Results: Network-level structural measures derived from the exponential threshold approach exhibited superior quality than those derived from other SNA approaches. The EHR communication network structures mediated the effect of care complexity on survival time: the average mediation effect was estimated to be 329 days (roughly 0.9 years, p-value < 0.0001). On average, EHR communication network structures mediated 7.89% of the total effect of care complexity on survival time, which supports the potential to leverage EHR communication network structures for cancer care interventions. There was no evidence that EHR communication network structures mediated the association between care complexity and ED visits.

Key Words: Cancer care teams, team communication, information sharing, EHR, patient outcomes, methods

2. PURPOSE (OBJECTIVES OF THE STUDY)

Electronic health records (EHR) have been adopted by over 98 percent of US hospitals.[1] The widespread adoption of EHR is changing how healthcare professionals (HCPs) deliver care and communicate with each other. Although evidence suggests that EHR use was associated with increased adherence to guidelines, enhanced clinical surveillance, and decreased medication errors,[2] the impact of EHR use on communication and teamwork among HCPs is not well understood.[3] How EHR transforms team-based care is identified as a high-priority research area by the National Academy of Medicine, Agency for Healthcare Research and Quality (AHRQ), and President's Cancer Panel for generating and applying new evidence to facilitate the effective and efficient collection, flow, and use of health information in care delivery.[4-6]

The literature indicates that we know little about how EHR use affects team communication in health care.[7, 8] From a patient's perspective, a care team consists of all HCPs who provide care to the same patient. Members of the care team often work at different times and in different locations, and increasingly use EHR to communicate care-related information. It is difficult to study such virtual care teams because they have elastic boundaries and emergent communication patterns. As EHR becomes a primary tool for sharing information and virtual team experience continues to intensify, we need to understand how HCPs process and share information in EHR to develop evidence-based practices for patient-centered care.

The objective of this project is to develop methods for measuring EHR communication networks, defined as EHR-based information sharing connections among HCPs,[9] in virtual care teams and examine the relationship between EHR communication networks and care quality. As an information repository, EHR serves a critical role in connecting virtual care teams' transactive memory system (TMS), which is a set of individual memories connected by communication links between them.[10] We will analyze complex communication patterns using social network analysis (SNA), which has been successfully applied to studying collaborative behaviors in care delivery and other team settings.[11] The project's specific aims are:

Specific Aim 1: Develop and compare methods for measuring EHR communication networks in virtual care teams for breast, colorectal, and non-small cell lung cancer patients.

Specific Aim 2: Examine associations between EHR communication network structures and these patient outcomes: a) 30-day re-admissions and emergency department (ED) visits; b) one-year utilization of inpatient and ED services; and c) one-year mortality.

3. SCOPE (BACKGROUND, CONTEXT, SETTINGS, PARTICIPANTS, INCIDENCE, PREVALENCE)

Cancer care routinely is delivered by diverse teams of HCPs who engage in complex communication and interactions across care settings.[12] The widespread adoption of EHR has greatly increased the amount of time that HCPs spend on EHR, writing and reviewing notes, orders, and other care-related information. EHR has become a primary communication tool for sharing care-related information between providers.[13] The intra-EHR communication is particularly important for virtual care teams because members of virtual teams often cannot effectively identify or communicate with one another using traditional methods.[14] Health IT experts argue that EHR has the potential to extend the reach of care teams, support team communication across the care continuum, and facilitate interconnected and coordinated care delivery.[15] However, we are only at an early stage of understanding how EHR use affects team communication and effectiveness.

From a team-effectiveness perspective, there are at least three factors contributing to the complexity of EHR communication: elastic boundaries of virtual care teams; team communication challenges;

and unintended consequences of EHR. First, with the segmentation of patient care by location and time, most cancer care teams are virtual teams with elastic boundaries influenced by both systematic factors (e.g., workflow, geographic and temporal distances) and idiosyncratic factors (e.g., patient circumstance and needs). It is difficult to identify who is on a patient's care team using traditional methods. Two recent reviews noted that little had been published on relationships between team composition, function, and effectiveness in cancer care.[16, 17]

Second, effective and efficient communication in care teams is crucial but challenging, especially when the team consists of many HCPs with diverse expertise who are distributed across different parts of the complex delivery system. Prior research suggests that team communication challenges are rooted in inherent barriers for group information processing,[18] ineffectiveness of computer-mediated communication,[19] and misalignment between the organization of the delivery system and the need for team-based coordination.[20]

Third, the team communication challenges are temporarily intensified during the transition to the EHR systems partly due to design flaws (e.g., lack of support for team functions[14]) and the mismatch between system features and HCPs' information needs (e.g., information overload and fragmentation[21]). With the increasing evidence of EHR's unintended consequences, experts are rejecting the ideas that health information challenges can be solved with more health IT or "proper" health IT implementation.[22] Instead, efforts are needed to characterize complex team structures, communication processes, and factors that enable effective teamwork in the new human-technological ecosystem to support high-quality, patient-centered care.

Previous research has examined collaboration and communication networks among HCPs following the patient-sharing approach, which infers stronger collaboration or information sharing between providers if they share more patients.[23, 24] In this study, we adopted a ***patient-centric approach*** to measure information sharing in teams using HCPs' direct access to the same patient's EHR record. First, this approach provides a stronger inference of communication specific to a patient's care and allows an examination of network structures across different patients and their care teams. Second, we draw on recent advancement in SNA methods to infer underlying team communication patterns from EHR access logs, which contain rich, temporal and directional information on providers' communication (information encoding and retrieval) activities. Our methods depict communication networks following naturally occurring clinical processes, and can be adapted to construct team communication networks for different types of patients and care settings. We expect that the proposed research will make significant methodological contributions to health IT research by focusing on team communication structures in EHR systems.

Our study was conducted using a patient sample receiving care at the Virginia Commonwealth University (VCU) Massey Cancer Center, an NCI-designated cancer center treating a large and diverse patient population (over 15,000 patients per year). At the Massey Cancer Center, cancer specialists collaborate in multidisciplinary teams to offer one-stop consultations and highly coordinated, unified care. The teams work together to guide each patient through every stage of care. Massey pioneered the region's multidisciplinary approach to cancer care, which combines the expertise of many doctors.

4. METHODS (STUDY DESIGN, DATA SOURCES/COLLECTION, INTERVENTIONS, MEASURES, LIMITATIONS)

Study Design, Sample, and Data Sources

This study used a retrospective observational design with no intervention. We identified the patient sample from the VCU Massey Cancer Center's Cancer Registry using the following inclusion criteria:

- Medicare patients

- Diagnosed with Stage I-IV breast, colorectal, or non-small cell (NSC) lung cancer
- Diagnosed between January 1, 2012 and December 31, 2017
- Received all or part of first-course cancer treatment at Massey Cancer Center

We identified 1,307 unique patients who met our inclusion criteria. Of this sample, 520, 188, and 599 patients were diagnosed with breast, colorectal, and NSC lung cancer respectively. Table 1 summarizes the actual enrollment numbers and inclusion of women and minorities, indicating 34% of the patients were African American and 70% were women.

Table 1. Cumulative (Actual) Enrollment

Racial Categories	**Ethnic Categories**						**Total**
	Not Hispanic or Latino			Hispanic or Latino			
	Female	Male	Unknown/ Not reported	Femal e	Male	Unknown/ Not reported	
American Indian/ Alaska Native	2	1	0	0	0	0	3
Asian	3	2	0	1	0	0	6
Black or African American	327	117	0	0	0	0	444
White	569	265	0	3	0	0	837
Other	3	6	0	1	1	0	11
Unknown	2	3	0	1	0	0	6
Total	906	394	0	6	1	0	1307

Table 2 summarizes our data sources. We extracted data from three sources: 1) the Massey Data Analysis System (MDAS), which had been linked to the VCU Cancer Registry and Social Security Death Index, provided data on patient demographics, diagnosis, treatment, comorbidity, and mortality; 2) EHR access logs were extracted from VCU Health's Cerner EHR system, which provided time-stamped information on HCPs' digital interactions with patients' records and with other HCPs; and 3) we requested Medicare Claims Research Identifiable Files from CMS to curate comprehensive data on patient utilization of inpatient and outpatient services after their cancer diagnosis.

Table 2. Data Sources

	MDAS	**EHR System**	**Medicare Claims RIF**
Patient Data			
Unique Identifiers	MRN, SSN, patient study ID	MRN, patient study ID	SSN, patient study ID
Demographics	Age, gender, race/ethnicity, insurance status	Age, gender, race/ethnicity, insurance status	Age, gender, race/ethnicity, insurance status
Diagnosis and Treatment	Cancer diagnosis date, cancer site, AJCC cancer stage, date of surgery, radiation, and medical treatment, date of discharge		ICD-9 & ICD-10 Codes
Comorbidities	Charlson Comorbidity Index		
Patient Outcomes	Date of death		Date of re-admission and ED visit
Health Care Professional (HCP) Data			
Unique Identifier		HCP user ID, HCP study ID	
Provider Characteristics		Professional role	
Access Events		Date, time, duration, and type (encoding/retrieval) of access	

The VCU Massey Cancer Center Informatics Core (CIC) analyst applied encryption protocols to replace identifiable data with generated patient and HCP study ID and de-identified the data according to the rigorous de-identification protocol. This project was approved by VCU's and University of Iowa's institutional review boards.

Measures and Analyses

We measured EHR communication networks in virtual care teams using EHR access logs between cancer diagnosis and 60 days after diagnosis for each patient. As described in our pilot study,[25] this time window was chosen to capture EHR communication amongst HCPs involved in planning and initiating cancer treatment as research suggested that treatment was typically initiated within 30 days of diagnosis for the majority of breast, colorectal, and lung cancer patients.[26-28]

For each patient we constructed an inter-professional EHR communication network based on the EHR access events performed by all HCPs involving each patient's care during the first 60 days after cancer diagnosis. The access events were classified into two types, either sending information to or retrieving information from the EHR system. In the EHR communication networks, a node represents an HCP, and a directed edge which connects two nodes – the sender to the receiver of the edge – represents information sharing between two HCPs.

For Specific Aim 1, we tested multiple approaches in SNA for measuring topological structures of the temporal EHR communication networks captured in the access logs, including a weighted and directed network based on the inverse of average time between a sender HCP's sending events and a retriever HCP's earliest subsequent retrieving event,[29] a modified exponential-threshold network,[30] and a multivariate marked Hawkes process network.[31] We compared how these different methods affect the constructed networks by computing and comparing the correlations between network-level structural measures and patient-level covariates.[32]

After constructing the EHR communication networks, we computed key network-level structural measures to describe the topology of the networks (summarized in Table 3). In order to make these measures comparable between cancer patients' networks, we computed the conditional uniform graph (CUG) quantile[33] for each measure and used these values rather than the raw measures for our subsequent analyses. The CUG quantile acts as a measure of how much non-random structure exists in the network.

Table 3. Network Structural Measures

Measure	Description	Mean (SD)
Size	Number of nodes.	96.69 (83.30)
Density	The ratio of the number of edges to the number of possible edges.	0.62 (0.09)
Out-Degree Centralization	A measure of the extent to which edges are disproportionately sent from a single node.	0.99 (0.05)
In-Degree Centralization	A measure of the extent to which edges are disproportionately received by a single node	0.84 (0.28)
Closeness Centralization	A measure of the disparity between a single node and all remaining nodes in how quickly information can be dispersed to all others.	0.97 (0.15)
Betweenness Centralization	A measure of the disparity in the volume of information that passes through a single node compared to information flow through the remaining nodes.	0.89 (0.25)
Assortativity Based on Degree	The extent to which nodes with high (low) connectivity engage in information flow with other nodes with high (low) connectivity.	0.33 (0.33)
Assortativity Based on Role	The extent to which information flows between nodes of the same HCP role (e.g., physician, nurse).	0.57 (0.27)

For Specific Aim 2, we examined the associations between EHR communication network structures and patient outcomes using a causal mediation analysis framework (see Figure 1) of Imai et al.[34] We analyzed two patient outcomes: 1) **Survival time** was measured as the number of days between 60 days after diagnosis and the death date. For patients who survived at the end of the study period, survival time was right censored at the last day of data extraction (1/31/2021); 2) **ED visits** was measured as a binary variable indicating whether or not a patient had ED visits between 60 days and 1 year after diagnosis. We first measured the count of ED visits as an outcome and then dichotomized it due to zero-inflated and highly skewed distribution. The following hypotheses were tested.

Hypothesis 1. Care complexity, as measured by patient's age, Charlson Comorbid Index (CCI), cancer site, and cancer stage, is associated with patient outcomes.

Hypothesis 2. Cancer care team's EHR communication network structure is associated with patient outcomes.

Hypothesis 3. Cancer care team's EHR communication network structure partially mediates the association between care complexity and patient outcomes.

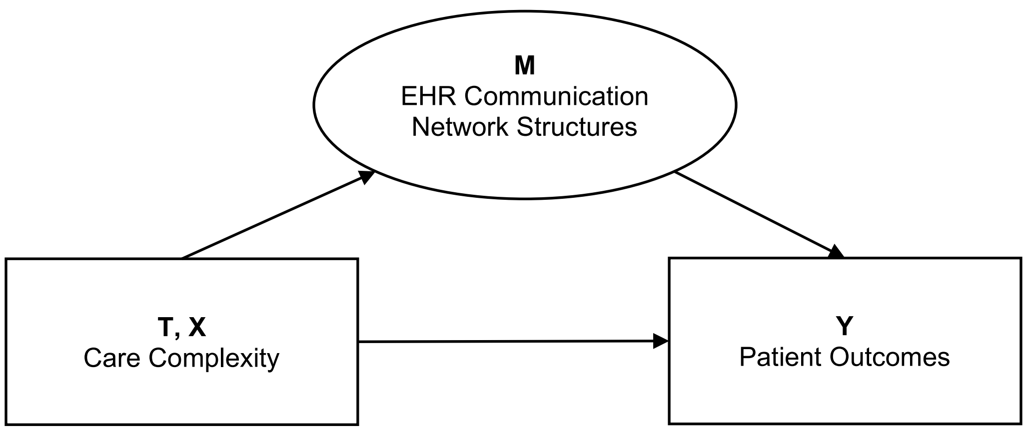

Figure 1. Relationships between Care Complexity, EHR Communication Network Structures, and Patient Outcomes

Our hypotheses imply that there is an effect of care complexity on patient outcomes, and that these effects are partially mediated through the EHR communication network structures. We ran a mediation analysis to test the direct and indirect effect of care complexity on patient outcomes. This analysis consisted of two distinct parts. First, we used a supervised approach to construct both a network structure and a care complexity composite variable. Second, these two composites were then used in a mediation analysis using the framework of Imai et al.[34] These two steps are described below, and Figure 2 provides a schematic of the two-step procedure.

To ensure valid inference from our mediation analysis, we split the patient-level data into (1) a training dataset (25% of the data) in which composite variables were trained, and (2) a holdout dataset (75% of the data) used for the mediation analysis. When splitting the data, stratification based on cancer sites and censored status of survival time/ED visits was applied to avoid imbalance. A composite variable for care complexity was constructed using a linear combination of age, CCI, cancer stage, and cancer site; categorical variables were transformed using one-hot encoding. The coefficients of the linear combination were obtained by taking the regression coefficients from the training models where we fitted an accelerated failure time (AFT) model for the survival time and a logistic regression model for ED visits in the training dataset. These regression coefficients were then used to construct a care complexity composite variable for the individuals in the holdout dataset. In the same manner, we constructed a composite variable for the network structure using the variables in Table 3 except indegree centralization and closeness centralization, which were excluded due to lack of variation. We then implemented a mediation analysis, involving fitting two models: 1) the first was an AFT predicting survival time or a logistic model predicting ED visits using the cancer complexity and network structure composite variables as covariates. The second was a linear regression model predicting the network structure composite using the cancer complexity composite as a covariate. In both models, we controlled for gender, race, payer type, and treatment regimens. We then estimated and computed confidence intervals for the mediation effects, direct effects, and proportion mediated. The mediation analysis was performed using the mediation package in R.

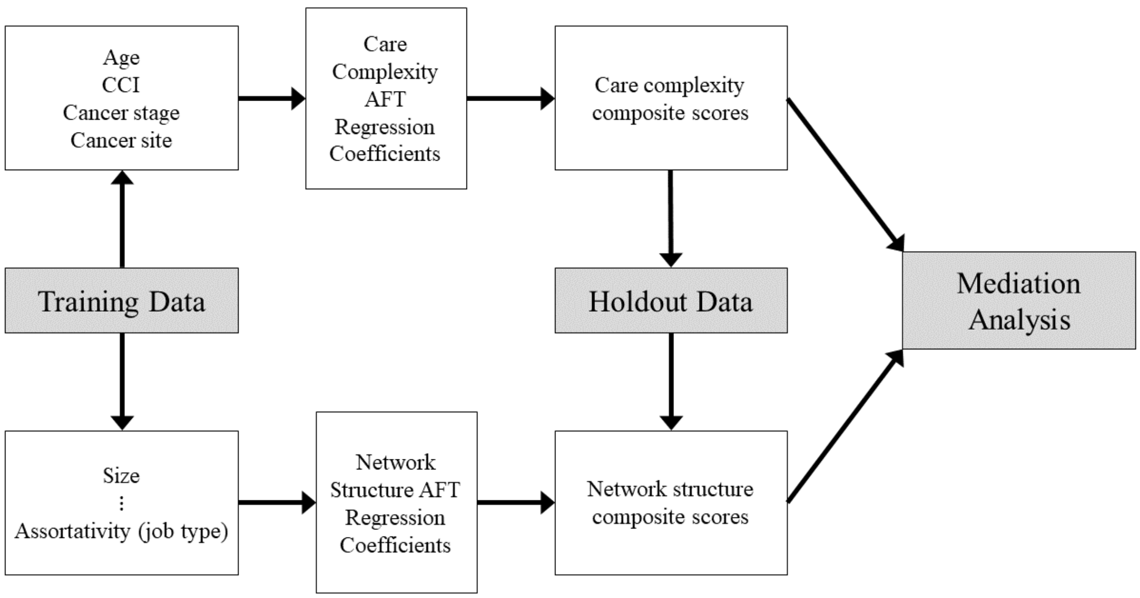

Figure 2. A Schematic Illustration of the Two-Stage Procedure of Mediation Analysis

Limitations

First, as an exploratory study, our sample includes only patients treated at a single academic medical center. Context-specific factors such as the EHR system and workflow implemented at VCU Health would affect generalizability of our findings. Second, we tested associations between patient outcomes and global EHR communication network structures. These global network structures, while well developed in the SNA literature to capture the global network topology, are general measures not informed by team or communication theories. Thus, our ability to develop specific team or communication strategies is constrained. Third, because our main goal was to develop and test the methods for measuring EHR communication networks, we did not aim to develop strategies or interventions to improve care outcomes such as survival time and ED visits. Future research can expand to multi-site studies to gauge the generalizability of our findings, construct theory-informed targeted team network measures, and move towards developing practical strategies and interventions to improve cancer care team communication and patient outcomes.

5. RESULTS (PRINCIPAL FINDINGS, OUTCOMES, DISCUSSION, CONCLUSIONS, SIGNIFICANCE, IMPLICATIONS)

Specific Aim 1: Develop and compare methods for measuring EHR communication networks in virtual care teams for breast, colorectal, and non-small cell lung cancer patients.

Holme[29] demonstrated that using an exponential threshold approach to construct a static network from temporal data retains most relevant information. We adapted this approach to our study context by constructing weights for each directed communication edge between two HCPs in the following way. For a given directed pair of HCPs i and j, we looked at each EHR sending event from i and found the earliest subsequent EHR retrieving event by j and recorded the time duration between two events, D; if no such retrieving event occurred in the data, we set D to be ∞. We then summed each of these durations using exponential decay terms parameterized by a threshold τ; that is, we summed terms of the form $e^{-D/\tau}$. This can be conceptualized as summing the number of times i sent information that was received by j, where each informational transaction is penalized according to the time required for j to receive the information. The threshold parameter τ effectively determines the time window for a meaningful informational transaction to take place; a larger τ implies a longer window/less urgency, whereas a smaller τ implies a smaller window/more urgency.

We compared the correlations of patient-level covariates including cancer site, cancer stage, and treatment regimens with network-level structural measures derived from the exponential threshold approach as well as from two other approaches, the inverse of average time approach and the multivariate marked Hawkes process.

Principal Findings: Network-level structural measures derived from the exponential threshold approach exhibited superior quality than those derived from the other two approaches as they showed meaningful variations across patients with different cancer and care characteristics and significant associations with these characteristics.

Specific Aim 2: Examine associations between EHR communication network structures and patient outcomes

To draw clear inferences, we examined associations between EHR communication network structures in virtual care teams and patient outcomes using an analytical sample in which patients met the following additional criteria: 1) received all of their first-course cancer treatment at VCU Health; and 2) survived at least 60 days after diagnosis. The analytical sample included 217 breast cancer, 124 colorectal cancer, and 370 lung cancer patients (N=711). Among these patients, 363 had died (51%). We split the analytical sample into a training (N=175) and a testing/hold-out set (N=536).

Survival Time as the Outcome: Table 4 summarizes the coefficients in the AFT model with EHR communication network structure, care complexity, and control variables using the full analytical data set. The overall effect of network structure played a significant role in a cancer patient's survival time even after accounting for cancer characteristics, demographics, and treatment regimens (p-value < 0.001), providing evidence supporting Hypothesis 2. Under 0.05 significance level, EHR communication network size and betweenness centralization had significant effects on patients' survival time. The multiplicative effect of network size was smaller than 1, indicating that larger networks were associated with shorter survival time. The multiplicative effect of betweenness centralization was larger than 1, indicating that more centralized communication networks were associated with longer survival time. Controlling all the other factors, patients with NSC lung cancer experienced shortest survival time (49% shorter than breast cancer patients), followed by colorectal cancer (38% shorter than breast cancer patients). Higher cancer stage and older patient age tended to decrease the survival time. Condition on same cancer type and age and comparing with patients with stage I cancer, patients with stage II cancer on average experienced 43% shorter survival time, patients with stage III cancer on average experienced 66% shorter survival time, and patients with stage IV cancer on average experienced 85% shorter survival time. A one-year increase in age shortened the survival time by 3%.

Table 4. AFT Model with EHR Communication Network Structures and Patient Characteristics Predicting Survival Time

	Multiplicative Effect on Survival Time	**95% CI**		**P-Value**
EHR Communication Network Structure				
Size	1.00	1.00	1.00	0.00004
Density	0.46	0.12	1.85	0.28
In-Degree Centralization	0.87	0.58	1.32	0.53
Betweenness Centralization	2.71	1.51	4.85	0.0008
Assortativity Based on Degree	1.31	0.95	1.80	0.10
Assortativity Based on Role	1.00	0.70	1.44	0.99
Cancer Site (Ref = Breast)				
Colorectal	0.62	0.43	0.91	0.015
Lung	0.51	0.35	0.73	0.0002
Cancer Stage (Ref = Stage I)				
Stage II	0.57	0.42	0.78	0.0004
Stage III	0.34	0.25	0.46	< 0.0001
Stage IV	0.15	0.11	0.20	< 0.0001
Control Variables				
CCI	0.94	0.90	0.98	0.005
Age	0.97	0.96	0.98	< 0.0001
Gender (Male)	0.86	0.70	1.06	0.17
Race (White)	1.10	0.90	1.35	0.35
Payer Type	0.95	0.88	1.02	0.18
Treatment Regimen (Chemo)	1.54	1.20	1.96	0.0006
Treatment Regimen (Surgery)	1.67	1.21	2.32	0.002
Treatment Regimen (Radiation)	0.82	0.64	1.05	0.123

For the mediation analysis, we used the first and third quartiles of the care complexity composite score to evaluate the mediation effects. The first quartile corresponds to high care complexity and shorter expected survival time, which is the treatment group; and the third quartile corresponds to low care complexity and longer expected survival time, which is the control group. The results of the causal mediation analysis are shown in Table 5.

Table 5. Results from the Mediation Analysis Using Survival Time as the Outcome, Cancer Complexity as the Treatment Variable, and EHR Communication Network Structure as the Mediator

	Estimation	**95% CI**		**P-Value**
Mediation Effect (Low CC*)	-511.4	-914.3	-206.4	<0.0001
Mediation Effect (High CC)	-146.7	-268.1	-61.7	<0.0001
Average Mediation Effect	-329.0	-581.8	-135.6	<0.0001
Direct Effect (Low CC)	-3897.0	-5156.2	-2822.3	<0.0001
Direct Effect (High CC)	-3532.3	-4601.0	-2595.4	<0.0001
Average Direct Effect	-3714.7	-4852.0	-2704.8	<0.0001
Total Effect	-4043.7	-5330.0	-2937.0	<0.0001
Proportion Mediated (Low CC)	12.26%	6.02%	21.0%	<0.0001
Proportion Mediated (High CC)	3.52%	1.59%	7.0%	<0.0001
Average Proportion Mediated	7.89%	3.89%	14%	<0.0001

*CC = cancer complexity

Principal Findings: Changing from low care complexity to high care complexity had an average direct effect, decreasing expected survival time by 3714.7 days (roughly 10 years, p-value < 0.0001), thereby providing evidence in support of Hypothesis 1.

The EHR communication network structures mediated the effect of care complexity on survival time: the average mediation effect was estimated to be 329 days (roughly 0.9 years, p-value < 0.0001), thereby providing evidence in support of Hypothesis 3. For patients with low care complexity, should their care teams' EHR communication networks shift to reflect structures similar to those of patients with high care complexity and shorter survival time (e.g., smaller and more centralized), we would expect the survival time to decrease by 511.4 days (roughly 1.4 years, p-value < 0.0001). For patients with high care complexity, should their care teams' EHR communication networks shift to reflect structures similar to those of patients with low care complexity and longer survival time, we would expect the survival time to increase by 146.7 days (roughly 0.4 years, p-value < 0.0001).

For patients with low care complexity, 12.26% of care complexity's total effect (the sum of direct and mediated effects) was mediated by care teams' EHR communication network structures. For patients with high care complexity, this proportion is 3.52%. On average, EHR communication network structures mediated 7.89% of the total effect of care complexity.

ED Visits as the Outcome: We estimated the same mediation model for ED visits as the outcome. The results are shown in Table 5.

Table 6. Results from the Mediation Analysis Using ED Visits as the Outcome, Cancer Complexity as the Treatment Variable, and EHR Communication Network Structure as the Mediator

	Estimation	**95% CI**		**P-Value**
Mediation Effect (Low CC*)	-0.002	-0.011	0.010	0.552
Mediation Effect (High CC)	-0.002	-0.008	0.000	0.552
Average Mediation Effect	-0.002	-0.001	0.000	0.554
Direct Effect (Low CC)	-0.049	-0.081	-0.010	0.004
Direct Effect (High CC)	-0.048	-0.081	-0.010	0.004
Average Direct Effect	-0.048	-0.081	-0.010	0.004
Total Effect	-0.050	-0.084	-0.020	0.002
Proportion Mediated (Low CC)	4.24%	-13.82%	26.0%	0.554
Proportion Mediated (High CC)	3.01%	-10.95%	23.0%	0.554
Average Proportion Mediated	3.62%	-12.49%	25.0%	0.554
*CC = cancer complexity				

Principal Findings: Care complexity had a significant direct effect on the odds of having ED visits between 60 days and 1 year after cancer diagnosis. The average direct effect was -0.048, indicating that comparing to patients with high care complexity, patients with low care complexity had 5% lower odds of having ED visits (odds=0.953, p-value < 0.01). However, there was no evidence that EHR communication network structures mediated the association between care complexity and ED visits.

Our primary findings have been summarized in a manuscript that is currently being prepared for a submission to Journal of the National Institute of Cancer.

> Zhu X, Li H, Sorensen E, Sewell D, Skoro N, Mishra V, Dow A, Matin K, Tu SP. Effects of EHR Communication Networks in Cancer Care Teams on Survival Time and ED Visits. *Working Paper in Preparation for Submission.*

Practical Implications and Future Research

Our principal findings that EHR communication network structures predict patient survival time and that EHR communication network structures mediate the effect of care complexity on survival time have important practical implications. Unlike care complexity (cancer site, cancer stage, age, and comorbidity presented at the time of diagnosis) that are mostly irreversible at the point of care, care teams' EHR communication network structures are a modifiable dimension of the care delivery system. Our findings suggest: 1) several EHR communication network structures, including network size and betweenness centralization, have significant effects on patients' survival time such that smaller and more centralized EHR networks are associated with longer survival time; 2) EHR communication network structures on average mediate 7.89% of the total effect of care complexity, which can be translated to an increase of survival time for 329 days or 0.9 years; and 3) we have more potential to improve outcomes through changing the EHR network structures for patients with low care complexity (511.4 days of potential increase in survival time compared to 146.7 days for patients with high care complexity).

Our findings support the potential to leverage EHR communication network structures for cancer care interventions: 7.89% of the total effect of care complexity on survival time was mediated through the global EHR network structures, an effect size comparable to other interventions (e.g. team training) that aim to improve interprofessional teamwork in healthcare.[35]

In a follow-up study recently funded by the National Cancer Institute (NCI, grant # R01 CA273058), our team builds on the novel evidence developed in this R21 project and leverages SNA and machine learning-assisted visual analytics to extend our research from general EHR network structures to theory-informed, targeted multi-team system (MTS) communication structures. This follow-up R01 project will address the issues of generalizability (with a multi-site study design) and targeted team network measures (with a specific aim to develop new, theory-informed measures of within- and between-group EHR communication in cancer care MTS), and advance towards developing an intervention to improve EHR communication in cancer care (with a specific aim to develop machine learning-assisted visual analytics and prototype tools to characterize and predict patients with EHR communication structures associated with poor outcomes).

6. LIST OF PUBLICATIONS AND PRODUCTS (BIBLIOGRAPHY OF OUTPUTS) FROM THE STUDY

Zhu X, Li H, Sorensen E, Sewell D, Skoro N, Mishra V, Dow A, Matin K, Tu SP. Effects of EHR Communication Networks in Cancer Care Teams on Survival Time and ED Visits. *Working Paper in Preparation for Submission.*

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