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Authors
Tu, Shin-Ping
Garcia, Brittany
Zhu, Xi
et al.

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COMMENTARY

Learning Health Systems

Patient care in complex Sociotechnological ecosystems and learning health systems

Shin-Ping Tu[1] | Brittany Garcia[1] | Xi Zhu[2] | Daniel Sewell[3] | Vimal Mishra[1] | Khalid Matin[4] | Alan Dow[4]

[1]Department of Internal Medicine, University of California, Davis, Sacramento, California, USA
[2]Department of Health Policy and Management, University of California, Los Angeles, Los Angeles, California, USA
[3]Department of Biostatistics, University of Iowa, Iowa City, Iowa, USA
[4]Department of Internal Medicine, Virginia Commonwealth University, Richmond, Virginia, USA

Correspondence
Shin-Ping Tu, Department of Internal Medicine, University of California, Davis, 4150 V Street, Suite 2400, Sacramento, CA, 95817, USA.
Email: sptu@ucdavis.edu

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Abstract
The learning health system (LHS) model was proposed to provide real-time, bi-directional flow of learning using data captured in health information technology systems to deliver rapid learning in healthcare delivery. As highlighted by the landmark National Academy of Medicine report "Crossing the Quality Chasm," the U.S. healthcare delivery industry represents complex adaptive systems, and there is an urgent need to develop innovative methods to identify efficient team structures by harnessing real-world care delivery data found in the electronic health record (EHR). We offer a discussion surrounding the complexities of team communication and how solutions may be guided by theories such as the Multiteam System (MTS) framework and the Multitheoretical Multilevel Framework of Communication Networks. To advance healthcare delivery science and promote LHSs, our team has been building a new line of research using EHR data to study MTS in the complex real world of cancer care delivery. We are developing new network metrics to study MTSs and will be analyzing the impact of EHR communication network structures on patient outcomes. As this research leads to patient care delivery interventions/tools, healthcare leaders and healthcare professionals can effectively use health IT data to implement the most evidence-based collaboration approaches in order to achieve the optimal LHS and patient outcomes.

KEYWORDS
learning health system, multiteam systems, team communication

1 | INTRODUCTION

The landmark National Academy of Medicine report "Crossing the Quality Chasm" highlighted that the U.S. healthcare delivery industry represents complex adaptive systems.[1,2] Complex adaptive systems include systems embedded in larger systems with control distributed among agents who are interconnected non-linearly through working relationships or other interactions. Given the complexity of teamwork,[3-10] the multiteam system (MTS) perspective offers a theoretical foundation to conceptualize interdependent work among multiple teams.[7] MTSs are networks of interdependent teams, also referred to as component groups, with collective system goals in addition to local goals.[11-13]

With cancer as a major public health problem worldwide and the second leading cause of death in the US, our research team has been interested in studying teamwork and the complex adaptive systems of healthcare delivery for cancer patients using electronic health record (EHR) data. In total, more than 1.9 million cancer cases will be diagnosed in 2023 and 609 820 Americans are expected to die of cancer.[14] A report on cancer care emphasized that 18 or more different clinical disciplines or roles may be involved in patients' comprehensive cancer care.[15] Furthermore, as many oncology specialists do not feel well-equipped to manage cancer patients' comorbidities, additional primary care and/or other specialist physicians are needed for patients with multiple and complex medical problems.[16] Optimizing patient care by high-performing teams that communicate and collaborate effectively[17,18] has been identified as a key strategy to improve health outcomes and patient experiences.[1,19] Yet there is surprisingly little evidence identifying MTS composition, even during the critical treatment planning period.[20]

Moreover, the generalizability of traditional team literature to complex MTSs is being challenged. Salas et al. highlighted the need to study teams "in the wild", instead of laboratory settings, using unobtrusive and robust measures collected over time.[21] In their review of MTS research, Shuffler and Carter found a heavy reliance on self-reported surveys, observations of teams in laboratory contexts, and limited repeated measures, all approaches constrained in their ability to reveal the richness of multiteam interactions, especially how interactions unfold over time to changing environmental and situational circumstances.[22] A recent study by Doose et al. found that 50% of newly diagnosed early breast, colorectal, and lung cancer patients received high-complexity MTS care[23] as defined by Zaccaro's theory-based classification of teams to classify MTS complexity.[24] As the authors noted, using SEER-Medicare data only identifies physicians or advanced practice providers, and other methodologies are needed to study varying MTS members providing care to cancer patients with multiple chronic conditions.

Research shows significant differences exist in the flow of communication by high- versus low-performing teams.[25-27] In particular, organizational research of communication and information processing has identified challenges confronted by complex MTSs.[22,28-32] As teams grow, a major challenge is ensuring inclusive communication. Hackman underscored "the larger a group, the more process problems members encounter in carrying out their collective work. [...] It's managing the links between members that gets teams into trouble."[33] Krackhardt called this constraint on communication and other networks the "Law of *n*-Squared" where *n* is the number of team members, and the number of potential links in a team's communication network increases quadratically with the number of people. In fact, it grows so rapidly (Figure 1) that the number of people to which each person could be linked quickly exceeds everyone's communication capacity.[34,35]

2 | OPPORTUNITIES FOR LEARNING HEALTH SYSTEMS

The LHS model was proposed to provide real-time, bi-directional flow of learning using data captured in health information technology systems to deliver rapid learning in healthcare delivery.[36-38] With EHRs now nearly ubiquitous in the US,[39] the LHS model highlights the importance of utilizing EHR data in tandem with external data sources to reduce care costs while allowing for the highest quality of care. However, for LHSs to work, population-level data is needed and EHRs are largely designed to provide individual, patient-level data. Furthermore, compiling EHR data alone or across multiple institutions is challenging and tedious. While health systems may use the same vendors to host their EHRs, interoperability between systems can vary due to features purchased and data structures.[40] Regarding the structure of EHR data, it is estimated that 80% of the data captured is unstructured or in free-text form, with emphasis on structured data for billing-related fields rather than clinical care fields.[41] Although Large Language Models are tapping the potential of free-text data in EHRs for direct patient care,[42] as Lee et al. noted in "The AI Revolution in Medicine," GPT-4's domain of expertise cannot be fully evaluated so unanticipated and potentially dangerous conclusions or suggestions continue to be the central problem.[43] However, there remains a large window of opportunity to tap into backend EHR data and unstructured fields to develop standardized data capture to guide team communication for patient care.

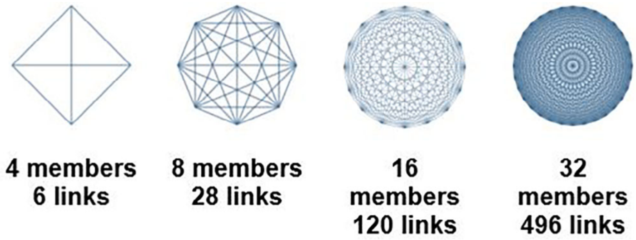

FIGURE 1 The number of potential links in a team's communication network increases quadratically with the number of people on the team. The number of links grows so rapidly that the number of people to which each person could be linked quickly exceeds everyone's communication capacity.

2.1 | Harnessing big data and the complexities of assessing healthcare delivery teams

"Digital traces" of teamwork interactions "in the wild" present opportunities to measure and study teamwork in MTSs.[22,44] As information repositories, EHRs provide "digital traces" of teamwork in natural settings and include (i) the ability of information holders and information retrievers to carry out their tasks asynchronously, (ii) reduce information processing load in a team because information holders may satisfy multiple requests by a single contribution to the repository, and (iii) direct access to "external" information from outside the team when multiple teams are all active users of the common repository.[45,46]

However, computer-mediated communication by distributed teams also presents significant challenges to information sharing for complex and interdependent tasks.[32,47,48] In particular, Kush et al. noted that being a member within multiple work groups can lead to weaker group identities.[32] And while geographically separated members can add novel knowledge to a group, the reliance on technology to communicate can create barriers to the successful transfer of this knowledge to other group members. A piece by the Harvard Business Review outlined key characteristics to consider when building a multidisciplinary and dispersed team.[48] These characteristics include identifying appropriate team members who are the best fit for virtual teamwork, have strong communication skills, and have high emotional intelligence; keeping the size of the team relatively small, with high-performing teams consisting of less than 13 members; creating sub teams with specific roles in the domains of core, operational, and outer project functions; appointing strong leadership who are able to build trust with team members, are encouraging of open dialogue, and are able to clarify project goals and guidelines; establishing in-person communication for key project moments such as project start-up, onboarding of new members, and major project milestones; and, lastly, utilization of a variety of technological communication platforms.[48]

In addition to the challenges specific to team structures and the flow of information between dispersed members, there are numerous other system-level factors that need to be considered to assess a team's ability to deliver care. The National Academy of Medicine's "Crossing the Quality Chasm" report emphasized a patient-centered approach to healthcare.[1] This proposed direction, along with interest among healthcare institutions and regulating bodies to track the quality of healthcare delivered has led to the implementation of patient satisfaction metrics.[49] The response from healthcare professionals regarding the use of patient satisfaction metrics has been mixed as these metrics have been inappropriately disaggregated and included in the determination of productivity as well as payments to incentivize physicians for quality service. In response, Centers for Medicare & Medicaid Services (CMS) emphasized the need for responsible use of the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey, as it was not designed to evaluate individual-level providers.[50] Additionally, patient satisfaction metrics can create racial and gender inequity related to unfavorable scoring and incentive payout, possibly as a result of implicit and institutional biases.[51]

With the push for patient-centered care and the expansion of telehealth efforts, the demand for immediate and face-to-face care, during and after standard work hours, has been on the rise. This trend has worsened the work-life balance for physicians with more: (a) personal time needed for patient care in the EHR, (b) errors, and (c) physician burnout and attrition.[52-57] Using EHR logging data, Arndt et al. found that family medicine physicians were spending approximately 4.5 hours (45%) of their workday in the EHR, with an additional 1.4 hours spent in the EHR outside of clinic hours or on the weekend.[58]

A recent report from the U.S. Department of Health and Human Services (HHS) highlighted major issues and concerns related to EHR burden including clinical documentation as well as the usability and user experience of health information technology.[59] A large body of research supports these pain points. To address these growing concerns, HHS also provided guidance for actions to implement and address these issues: reducing the regulatory burden of documentation; developing a process to address inconsistent data collection by federal, state, and local programs standardizing service orders and data; improving the user interface to match clinical workflow; and improving the value and usability of electronic clinical quality measures.[59]

With a growing and aging population in the U.S., including a large portion of physicians nearing retirement or choosing early retirement, the healthcare professional shortage will continue to worsen. The Association of American Medical Colleges (AAMC) projected that between 17 800 and 48 000 primary care physicians and between 21 000 and 77 100 non-primary care physicians will be lost by 2034.[60] This workforce reduction adds increased case load to an already stressed network of healthcare professionals, opening up further opportunity for errors and burnout.

Although a growing body of literature is documenting the role of EHRs in patient care inefficiencies, errors, and physician burnout,[52-57] Rosen et al. noted that information systems, such as EHRs, have the potential to support teamwork, and that research should apply MTS models to study and develop interventions that strengthen teamwork, especially between groups.[61] Experts emphasize that information processing complexity in large MTSs require coordination mechanisms that must leverage the structure and relative importance of different positions in the system.[62]

While research exists that utilizes EHR data, these studies have primarily focused on cognitive workflow or cognitive burden, communication patterns, and message volume and content, and do not involve a tangible solution to make use of backend user data collected in the EHR to assist in improving care delivery.[63-67]

2.2 | Theory-guided research and solutions

Although our new healthcare delivery ecosystem is rapidly changing the way healthcare professionals communicate, there is limited literature on how to optimize communication and information processing in MTSs.[68,69] In their Multitheoretical Multilevel Framework of Communication Networks, Contractor et al. identified nine families of social theories and their theoretical mechanisms that have been used to explain various organizational networks.[70] Four theoretical families with direct implications for teamwork in MTS are summarized in Table 1 with corresponding theoretical mechanisms. We briefly review key theoretical mechanisms that explain how individual and network factors may affect the effectiveness and efficiency of communication and information sharing in cancer care teams.

Proximity theories posit that people communicate better with those to whom they are physically close or within a reachable distance. The theory of electronic proximity extends this to the realm of various forms of electronic communication.[71] Coordination theory argues that proximity influences the amount and quality of interaction which in turn influences coordination.[72] Cognitive theories explore the role that meaning, knowledge, and perceptions play in communication and information sharing. Specifically, transactive memory systems theory and cognitive structure theory suggest that shared perceptions of the communication network and knowledge about where information/expertise is located facilitate effective communication and information search/retrieval in teams.[34,73]

TABLE 1 Multitheoretical multilevel framework of communication networks for teamwork.

Theories	Theoretical mechanisms	Survey measures	EHR SNA measures
Proximity theories	Influence of distance and accessibility • Information transfer distance • Information accessibility • Coordination by proximity	• Physical proximity • Electronic proximity • Reachability • Interaction frequency	• Closeness centralization • Reachability • k-shells
Cognitive theories	Shared perceptions and knowledge of information location • Effective information search and retrieval • Efficient network structure	• Ease to determine "who talks to whom" • Ease of knowledge and information search and retrieval	• Density • Global efficiency
Self-interest theories	Advantages in network positions • Control of information flow • Opportunities for coordination External drivers • Time, finance, and other self-interests	• Time allocation • Clinical workflow efficiency • Productivity measures • Revenue impact	• Clustering coefficient • Effective network size • Betweenness centrality
Consistency theories	Drive to reduce cognitive & other dissonance • Communication in role-based groups • Communication in structure-based groups	• Intra-group communication • Inter-group communication • Communication satisfaction	• Transitive triads • Assortativity • Community structure

Theories of self-interest focus on how people make choices that favor their personal preferences and desires. This theory is particularly helpful in explaining individual drivers behind certain communication and information-sharing behaviors. Cognitive consistency theories focus on the extent to which the attitudes, beliefs, opinions, and values of network members are governed by a drive toward consistency. This theory suggests that network members tend to form links with similar others (e.g., within the same professional group) to maintain cognitive balance and avoid cognitive dissonance, which in turn influences the level of satisfaction and commitment.

The concept is especially relevant for understanding teamwork in MTSs is a transactive memory system, a critical form of shared cognition defined as a set of individual memories connected by the communication that takes place between individuals.[73,74] Transactive memory systems can also be conceptualized as a communication network, with team members representing information agents and communication among them representing information links between the agents.[71,75,76]

Schakel argued that a transactive memory system is an antecedent to combining knowledge and capabilities to achieve team effectiveness, and that failure to develop an effective transactive memory system is one of the most common barriers to team success.[77] Transactive memory systems should reduce the cognitive load on individuals, enlarge the collective pool of expertise, and minimize redundancy.[31] However, the literature also raised concerns about transactive memory systems pertinent to EHRs including the following: (a) failure to capture important information, (b) diffusion of responsibility, and (c) limitations to the size of distributed memory systems, at which point tracking costs may outweigh memory gains.[6,73,76]

Of note, Gupta and Woolley's research found that working with many different group members across various projects negatively affected team performance by impairing the transactive memory system.[74] Their study also showed that access to team information mitigated this negative effect.[74] An important mechanism driving team performance, transactive memory system is a potential point of leverage for MTS interventions.

More recently, advances in the MTS literature have been made surrounding the identification of themes and patterns that are present among real-world cases of failed MTSs. Real-world cases of failed MTSs can range from extreme, high-stakes contexts such as the 2017 collision of three U.S. Navy vessels, resulting in the deaths of several Navy sailors and millions of dollars in damages,[78] to less extreme contexts such as the 2013 failed launch day for the Affordable Care Act website, which saw more than 250 000 users, of which only six were able to select a plan and submit an application.[79] Overall, a failed MTS can be defined as an MTS whose performance, in the face of challenges, resulted in a failure to achieve targeted distal goals.[80]

In their historiometric analysis of failed MTS performance, Campbell and colleagues[80] identified four major themes that were found across or seen as a contributing factor in known cases of MTS breakdown. Using the action subphases or team alignment behaviors (acting, monitoring, and recalibrating) at the within- and between-teams levels from Torres et al.[78] as the foundation for their evaluation, they noted that failing MTSs demonstrated an imbalance in within-team alignment behaviors more often than and at the expense of between-team alignment behaviors. Rationale for this relationship may be that within-team behaviors are more familiar, and therefore, less difficult to contribute to in comparison to between-team facilitations. The second theme noted among failing MTSs was that the full span of the action subphase was not employed, with subphase acting behaviors (behaviors related to goal striving and accomplishment) being the most dominantly engaged among these systems. While attempts were made to monitor and recalibrate, "wait-and-see" tracking was often the approach used, resulting in insufficient efforts for corrective action. The third theme identified was that boundary status (whether teams are within a single (internal) or multiple (external) organizations[81]), further increases the inefficiency of engaging in between-team behaviors, noting that external groups tended to turn to more inward activities as the crisis persisted. The final theme noted by Campbell is that goal type (physical goals that require physical skills or a tangible outcome; or intellectual goals, which require mental skills and new knowledge[24,82]) also further increases the pattern of insufficient between-teams behaviors. In particular, the full span of the action subphase occurred more often within physical MTSs but more often between intellectual MTSs, noting that the collaborative barriers may differ between physical and intellectual MTSs. To address these patterns among failed MTSs, Campbell suggests that entrainment, or the cyclical within-team alignment and between-team behaviors, is a key driver in whether an MTS succeeds or fails. As such, cues or a monitoring system, deployed in the monitoring phase should be adopted to allow for the adaptive shifting of task requirements and execution to meet target goals.

Additionally, there has also been a call in the literature for a way to measure team effectiveness. Building upon the team effectiveness model and incorporation of temporal processes described by Marks et al.,[10] Turner and colleagues[83] have laid out a team effectiveness model specifically for MTSs. Their model consists of two formulas that account for team characteristics at the MTS, component team, and individual levels of analysis, as well as for each temporal process (transition, action, interpersonal). Given the dynamic nature of team collaboration, the application of their model is ideal as it would allow for the assessment of the MTS patterns over time rather than assessing correlations at a single point in time. With the robust theory- and research-driven approaches noted here, our team has developed a clear path forward in advancing MTS communication and coordination in healthcare settings.

3 | DISCUSSION

As this is a newly emerging and complex area of inquiry, we found limited research on communication networks, information flow, information processing, and their implications for teamwork on patient care coordination and health outcomes. MTS experts have recommended greater use of network metrics to study MTSs,[24,84,85] and emphasized network features within and between groups. In contrast to the participant burden and reliability challenges of survey and observational data collection,[71,86-91] EHR access-logs capture all communication activities related to encoding and retrieving patient record information and surmount the constraints of traditional team research to study complex MTSs in natural healthcare settings. Research is urgently needed to understand and apply social network analysis (SNA) methods that innovatively measure within- and between-group EHR communication in healthcare MTSs and determine the impact of EHR communication network structures on patient outcomes.

To advance healthcare delivery science and promote LHSs, our team has been building a new line of research using EHR data to study MTS in the complex real world of cancer care delivery. Our first study of 100 surgical colorectal cancer patients had almost 2.5 million records of time-stamped EHR access logs from more than 6800 unique users.[92] Across all networks, healthcare professionals were connected to an average of 5.8 other professionals, but some were rarely connected with others while over 20 were very highly connected to over 100 other healthcare professionals. We also found substantial variations in size and structures among the 100 EHR communication networks.[93] Furthermore, the distributions of conditional uniform graph quantiles suggested that our network-construction technique captured meaningful underlying structures that were different from random unstructured networks.

Based on the literature and our study findings to date, we developed the framework illustrated by Figure 2 to further guide our research with a focus on communication, specifically information sharing in MTS, and new measures that need to be developed to advance teamwork for optimal patient care and outcomes.

Our current research (NIH R01 CA273058) aims to provide novel evidence of cancer care MTS communication and coordination in natural settings across multiple academic health systems using unobtrusive and robust “digital traces” of teamwork interactions.[21,22] We are leveraging SNA and machine learning (ML)-assisted visual analytics to extend our research from general EHR communication structures to theory-informed, targeted MTS network structures of breast, colorectal, and non-small cell lung cancer patients at three clinical sites that all use Epic EHRs.[55,94] Our research centers on one modifiable dimension of team communication, information sharing through EHRs, with these aims: (a) develop new measures of within- and between-group EHR communication in cancer care MTSs; (b) determine the associations of targeted EHR communication structures with cancer care quality outcomes; and (c) develop ML-assisted visual analytics and prototype tools to (i) characterize MTSs, and (ii) predict patients with EHR communication structures associated with poor quality outcomes.

Based on our research to date using EHR data, to deliver on the possibilities of rapid learning using health information technology data, LHSs need effective information sharing by their MTS members enabled through rigorous data analytics. Research that effectively addresses the communication and information-processing complexities of healthcare delivery is urgently needed. Our team chose to apply network science and visual analytics to study the most effective team structures and how best to modify existing collaborations in care to improve patient outcomes.

In addition to the architecture of workflows and systems on complex processes such as patient care, other areas of much-needed research to optimize teamwork in LHSs include the following: (i) usability testing of digital tools[95-97]; (ii) coupling of data and teams—does more shared data and analytics add efficiency to team interactions?; (iii) team roles as well as the knowledge, experience, and skillsets needed for our increasingly more complex and rapidly changing digital healthcare landscape; and (iv) decision making at the many levels and components of MTSs.

Of notable consideration is the role that leadership plays as it is a key component in the success or failure of multi-team collaboration. The leadership literature identifies key components that facilitate team coordination, including boundary spanning, risk taking, visioning, leveraging opportunity, adaptation, coordination of information flow,

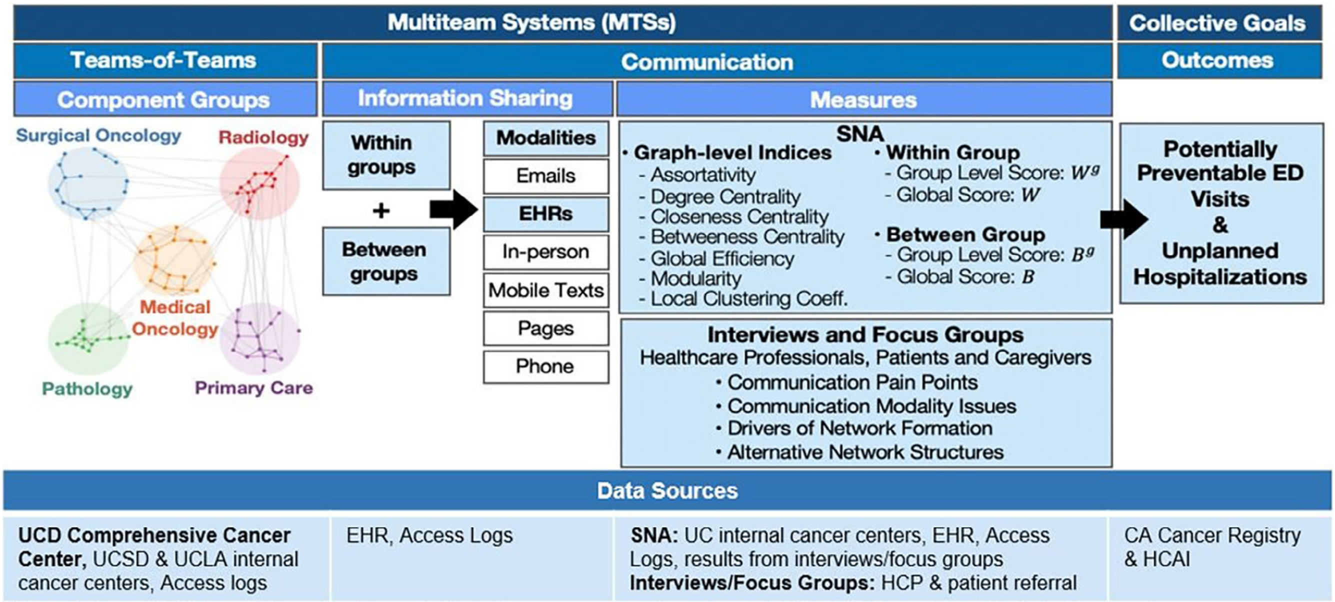

FIGURE 2 Communication in Multiteam Systems occur within groups and between groups. In patient care, communication and information-sharing increasingly occur through the EHR platform. Our research is developing novel measures, using SNA as well as qualitative methods, and studying their association with potentially preventable ED visits and unplanned hospitalizations. SNA = social network analysis; ED = emergency department; UCD=University of California, Davis; UCSD=University of California, San Diego; UCLA = University of California, Los Angeles; EHR = electronic health record; HCP = healthcare professional; HCAI=California Department of Health Care Access and Information.

and facilitation.[98] Traditional command-and-control leadership has shown less effectiveness than diverse team leadership that is supported by their respective organizations. Furthermore, hierarchical leadership structures limit the ability of "lower ranking" team members to voice opinions, make implementing change and innovation difficult, and contribute to gender and ethnic inequalities and discriminatory practices.[99] Diverse team leadership groups have demonstrated to be a characteristic of high-performing teams,[100] with greater success in innovation and outcomes.[101] To facilitate team leadership, the conceptual framework of boundary-spanning leadership (BSL),[102] defined as "leadership that bridges boundaries between groups in service of a larger organizational vision, mission, or goal,"[103] offers three strategies to align team members across multiple groups, including managing boundaries, forging common ground, and discovering new frontiers. Taken together, these three strategies allow teams to satisfy members' need for autonomy, unity, and advancement of interdependence through fostering innovative and creative solutions among group members.[104]

When applied to a public health context, BSL can provide a practical toolset to foster interprofessional collaboration and enhance the full patient care experience. As noted by Flick-Cooper et al., through their experience with multisite public health partnerships, they were able to successfully incorporate BSL tactics including on-site training with active coaching for team members and receipt of federal funding to assist with the implementation of BSL practices.[104] Similarly, in the United Kingdom, Hunt et al. found that incorporating a designated community and physical health coordinator with protected time to perform boundary-spanning activities, along with multi-disciplinary team meetings enhanced their team collaboration in the diversity and length of information exchanged and recorded, as well as the diversity in the division of tasks or responsibility between group members.[105] While research supports the importance of team leadership, healthcare entities largely continue to operate using the traditional hierarchical models of leadership. Hierarchical leadership in a healthcare setting or other "extreme action teams"[106] is necessary as it lets team members know who to look and defer to in a crisis event. However, Klein and colleagues[106] have noted that a hybrid leadership structure, referred to as a "deindividualized system of shared leadership", specific to these types of teams may prove more useful. This system, they argue, allows for dynamic delegation of the active leadership roles which facilitates learning and reliability among the more junior team members.

As these research directions bear fruit, including the latest advances in SNA and artificial intelligence, healthcare leaders and healthcare professionals can effectively use health information technology data to implement the most evidence-based collaboration approaches in order to achieve optimal LHS and patient outcomes.

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CONFLICT OF INTEREST STATEMENT

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ORCID

Brittany Garcia https://orcid.org/0000-0001-5351-3545

REFERENCES

1. Institute of Medicine. *Crossing the Quality Chasm: A New Health System for the 21st Century*. Washington, DC: National Academies Press; 2001:309-322.
2. Litaker D, Tomolo A, Liberatore V, Stange KC, Aron D. Using complexity theory to build interventions that improve health care delivery in primary care. *J Gen Intern Med*. 2006;21(2):S30-S34.
3. Taplin SH, Weaver S, Salas E, et al. Reviewing cancer care team effectiveness. *J Oncol Pract*. 2015;11(3):239-246.
4. Weaver S, Feirosa J, Salas E. The theoretical drivers and models of team performance and effectiveness for patient safe. In: Salas E, Frush K, eds. *Improving Patient Safety through Teamwork and Team Training*. New York, NY: Oxford University Press; 2012:3-79.
5. Ilgen DR, Hollenbeck JR, Johnson M, Jundt D. Teams in organizations: from input-process-output models to IMOI models. *Annu Rev Psychol*. 2005;56(1):517-543.
6. Kozlowski SWJ, Bell BS. Work groups and teams in organizations. In: Borman WC, Ilgen DR, Klimoski RJ, eds. *Handbook of Psychology*. Vol 12. New York, NY: John Wiley & Sons, Inc.; 2003:333-375.
7. DiazGranados D, Dow AW, Perry SJ, Palesis JA. Understanding patient care as a multiteam system. In: Shuffler ML, Rico R, Salas E, eds. *Pushing the Boundaries: Multiteam Systems in Research and Practice*. Vol 16. Bingley, ENG: Emerald Group Publishing Limited; 2014: 95-113.
8. Arrow H, McGrath JE, Berdahl JL. *Small Groups as Complex Systems: Formation, Coordination, Development, and Adaptation*. Thousand Oaks, CA: Sage Publications; 2000.
9. Kozlowski SW, Gully SM, Nason ER, Smith EM. Developing adaptive teams: a theory of compilation and performance across levels and time. In: Pulakos ED, ed. *The Changing Nature of Performance: Implications for Staffing, Motivation, and Development*. San Fransisco, CA: Jossey-Bass; 1999:240-292.
10. Marks MA, Mathieu JE, Zaccaro SJ. A temporally based framework and taxonomy of team processes. *Acad Manage Rev*. 2001;26(3): 356-376.
11. Mathieu JE, Marks MA, Zaccaro SJ. Multiteam systems. In: Anderson N, Ones DS, Sinangil HK, Viswesvaran C, eds. *Handbook of Industrial, Work and Organizational Psychology. Organizational Psychology*. Vol 2. London, England: SAGE Publications Ltd; 2001: 289-313.
12. Weaver SJ, Che XX, Petersen LA, Hysong SJ. Unpacking care coordination through a multiteam system lens. *Med Care*. 2018;56(3): 247-259.
13. Contractor N, Poole M. Conceptualizing the multiteam system as an ecosystem of networked groups. In: Zaccaro S, Marks M, DeChurch L, eds. *Multiteam Systems: An Organizational Form for Dynamic and Complex Environments*. New York, NY: Routledge Academic; 2011:193-224.
14. American Cancer Society. *Cancer Facts & Figures*. 2023.
15. Levit LA, Balogh E, Nass S, Ganz PA. Institute of Medicine. Delivering high-quality cancer care: charting a new course for a system in crisis. *Natl Acad Sci*. 2013.
16. Weaver SJ, Jacobsen PB. Cancer care coordination: opportunities for healthcare delivery research. *Transl Behav Med*. 2018;8(3): 503-508.
17. Earnest M, Brandt B. Aligning practice redesign and interprofessional education to advance triple aim outcomes. *J Interprof Care*. 2014;28(6):497-500.
18. Dossett LA, Hudson JN, Morris AM, et al. The primary care provider (PCP)-cancer specialist relationship: a systematic review and mixed-methods meta-synthesis. *CA Cancer J Clin*. 2017;67(2):156-169.
19. Dow AW, Zhu X, Sewell D, Banas CA, Mishra V, Tu S-P. Teamwork on the rocks: Rethinking interprofessional practice as networking. *J Interprof Care*. 2017;31(6):677-678.
20. Doose M, Verhoeven D, Sanchez JI, et al. Team-based care for cancer survivors with comorbidities: a systematic review. *J Healthc Qual*. 2022;44(5):255-268.
21. Salas E, Reyes DL, McDaniel SH. The science of teamwork: Progress, reflections, and the road ahead. *Am Psychol*. 2018;73(4):593-600.
22. Shuffler ML, Carter DR. Teamwork situated in multiteam systems: key lessons learned and future opportunities. *Am Psychol*. 2018; 73(4):390-406.
23. Doose M, Verhoeven D, Sanchez JI, McGee-Avila JK, Chollette V, Weaver SJ. Clinical multiteam system composition and complexity among newly diagnosed early-stage breast, colorectal, and lung cancer patients with multiple chronic conditions: a SEER-Medicare analysis. *JCO Oncol Pract*. 2023;19(1):e33-e42.
24. Zaccaro SJ, Dubrow S, Torres EM, Campbell LNP. Multiteam systems: An integrated review and comparison of different forms. *Annu Rev Organ Psych Organ Behav*. 2020;7(1):479-503.
25. Barczak GDW. Communications patterns of new product development team leaders. *IEEE Trans Eng Manag*. 1991;38(2):101-109.
26. Olson G, Herbsleb J, Reuter H. Characterizing the sequential structure of interactive behaviors through statistical and grammatical techniques. *Hum Comput Interact*. 1994;9(3):427-472.
27. Olson GM, Olson JS. Human-computer interaction: psychological aspects of the human use of computing. *Annu Rev Psychol*. 2003;54: 491-516.
28. Stasser G, Titus W. Pooling of unshared information in group decision-making - biased information sampling during discussion. *J Pers Soc Psychol*. 1985;48(6):1467-1478.
29. Stewart DD, Stasser G. Expert role assignment and information sampling during collective recall and decision making. *J Pers Soc Psychol*. 1995;69(4):619-628.
30. Larson JR Jr, Christensen C, Abbott AS, Franz TM. Diagnosing groups: charting the flow of information in medical decision-making teams. *J Pers Soc Psychol*. 1996;71(2):315-330.
31. Hollingshead AB. Retrieval processes in transactive memory systems. *J Pers Soc Psychol*. 1998;74(3):659-671.
32. Kush J, Williamson C, Argote L. Challenges and opportunities for group learning and group learning researchers. In: Mannix EA, Neale MA, Mannix EA, eds. *Research on Managing Groups and Teams: Looking Back, Moving Forwards: A Review of Group and Team-Based Research*. Vol 15. Bingley, ENG: Emerald Group Publishing Limited; 2012:209-243.
33. Hackman JR. *A Normative Model of Work Team Effectiveness*. New Haven, CT: Yale University, School of Organization and Management; 1983:2.
34. Krackhardt D. Constraints on the interactive organization as an ideal type. In: Heckscher C, Donnellon A, eds. *The Post-Bureaucratic Organization: New Perspectives on Organizational Change*. Thousand Oaks, CA: Sage; 1994:211-222.
35. Anthony S. Five ways to innovate faster. *Harvard Business Rev*. 2013;3.
36. Etheredge LM. A rapid-learning health system. *Health Aff (Millwood)*. 2007;26(2):w107-w118.
37. Friedman CP, Wong AK, Blumenthal D. Achieving a Nationwide learning health system. *Sci Transl Med*. 2010;2(57):57cm29-57cm29.
38. Greene SM, Reid RJ, Larson EB. Implementing the learning health system: from concept to action. *Ann Intern Med*. 2012;157(3): 207-210.

39. *Office of the National Coordinator for Health Information Technology. Percent of Hospitals, By Type, that Possess Certified Health IT*. 2017.
40. Bernstam EV, Warner JL, Krauss JC, et al. Quantitating and assessing interoperability between electronic health records. *J Am Med Inform Assoc*. 2022;29(5):753-760.
41. Kong HJ. Managing unstructured big data in healthcare system. *Healthc Inform Res*. 2019;25(1):1-2.
42. Wachter RM, Brynjolfsson E. Will generative artificial intelligence deliver on its promise in health care? *JAMA*. 2024;331(1):65-69.
43. Lee P, Goldberg C, Kohane I. *The AI Revolution in Medicine GPT-4 and beyond*. Harlow, England: Pearson Education; 2023.
44. Kozlowski SWJ. Enhancing the effectiveness of work groups and teams: a reflection. *Perspect Psychol Sci*. 2018;13(2):205-212.
45. Yuan YC, Fulk J, Monge PR. Access to information in connective and communal transactive memory systems. *Commun Res*. 2007;34(2):131-155.
46. Kalman ME, Monge P, Fulk J, Heino R. Motivations to resolve communication dilemmas in database-mediated collaboration. *Commun Res*. 2002;29(2):125-154.
47. Hollingshead AB, Brandon DP. Potential benefits of communication in transactive memory systems. *Hum Commun Res*. 2003;29(4):607-615.
48. Ferrazzi K. Getting virtual teams right. *Harv Bus Rev*. 2014;92:120-123.
49. Glickman SW, Schulman KA. The mis-measure of physician performance. *Am J Manag Care*. 2013;19(10):782-785.
50. Tefera L, Lehrman WG, Conway P. Measurement of the patient experience: clarifying facts, myths, and approaches. *JAMA*. 2016;315(20):2167-2168.
51. Sotto-Santiago S, Slaven JE, Rohr-Kirchgraber T. (dis)incentivizing patient satisfaction metrics: the unintended consequences of institutional bias. *Health Equity*. 2019;3(1):13-18.
52. McCann E. EHR still in play with US Ebola case. 2014. http://www.healthcareitnews.com/news/ehr-still-play-us-ebola-case Accessed February 3, 2017 2017.
53. Wachter R. *The Digital Doctor: Hope, Hype, and Harm at the Dawn of Medicine's Computer Age*. 1st ed. New York, NY: McGraw-Hill Education; 2015.
54. Murphy DR, Reis B, Kadiyala H, et al. Electronic health record–based messages to primary care providers: valuable information or just noise? *JAMA Intern Med*. 2012;172(3):283-285.
55. Quinn M, Forman J, Harrod M, et al. Electronic health records, communication, and data sharing: challenges and opportunities for improving the diagnostic process. *Diagnosis (Berl)*. 2019;6(3):241-248.
56. Rosenbaum L. Transitional chaos or enduring harm? The EHR and the disruption of medicine. *N Engl J Med*. 2015;373(17):1585-1588.
57. Varpio L, Rashotte J, Day K, King J, Kuziemsky C, Parush A. The EHR and building the patient's story: a qualitative investigation of how EHR use obstructs a vital clinical activity. *Int J Med Inform*. 2015;84(12):1019-1028.
58. Arndt BG, Beasley JW, Watkinson MD, et al. Tethered to the EHR: primary care physician workload assessment using EHR event log data and time-motion observations. *Ann Fam Med*. 2017;15(5):419-426.
59. The Office of the National Coordinator for Health Information Technology. *Strategy on Reducing Regulatory and Administrative Burden Relating to the Use of Health IT and EHRs*. 2020.
60. IHS Markit Ltd. *The Complexities of Physician Supply and Demand: Projections from 2019 to 2034*. Washington, DC: AAMC; 2021.
61. Rosen MA, DiazGranados D, Dietz AS, et al. Teamwork in healthcare: key discoveries enabling safer, high-quality care. *Am Psychol*. 2018;73(4):433-450.
62. Davison RB, Hollenbeck JR, Barnes CM, Sleesman DJ, Ilgen DR. Coordinated action in multiteam systems. *J Appl Psychol*. 2012;97(4):808-824.
63. Moy AJ, Hobensack M, Marshall K, et al. Understanding the perceived role of electronic health records and workflow fragmentation on clinician documentation burden in emergency departments. *J Am Med Inform Assoc*. 2023;30(5):797-808.
64. Park J, Zhong X, Dong Y, Barwise A, Pickering BW. Investigating the cognitive capacity constraints of an ICU care team using a systems engineering approach. *BMC Anesthesiol*. 2022;22(1):10.
65. Steitz BD, Sulieman L, Warner JL, et al. Classification and analysis of asynchronous communication content between care team members involved in breast cancer treatment. *JAMIA Open*. 2021;4(3):ooab049.
66. Steitz BD, Unertl KM, Levy MA. Characterizing communication patterns among members of the clinical care team to deliver breast cancer treatment. *J Am Med Inform Assoc*. 2020;27(2):236-243.
67. Sulieman L, Gilmore D, French C, et al. Classifying patient portal messages using convolutional neural networks. *J Biomed Inform*. 2017;74:59-70.
68. Horwitz LI, Detsky AS. Physician communication in the 21st century: to talk or to text? *JAMA*. 2011;305(11):1128-1129.
69. Wu R, Rossos P, Quan S, et al. An evaluation of the use of smartphones to communicate between clinicians: a mixed-methods study. *J Med Internet Res*. 2011;13(3):e59.
70. Contractor NS, Wasserman S, Faust K. Testing multitheoretical, multilevel hypotheses about organizational networks: An Analytic framework and empirical example. *Acad Manage Rev*. 2006;31(3):681-703.
71. Monge PR, Contractor NS. *Theories of Communication Networks*. New York, NY: Oxford University Press; 2003.
72. Okhuysen GA, Bechky BA. 10 coordination in organizations: An integrative perspective. *Acad Manag Ann*. 2009;3(1):463-502.
73. Wegner DM. Transactive memory: a contemporary analysis of the group mind. *Theories of Group Behavior*. New York, NY: Springer; 1987:185-208.
74. Gupta P, Woolley AW. Productivity in an era of multi-teaming. *Proc ACM Hum-Comput Interact*. 2018;2(CSCW):1-18.
75. Fulk J, Heino R, Flanagin AJ, Monge PR, Bar F. A test of the individual action model for organizational information commons. *Organ Sci*. 2004;15(5):569-585.
76. Kozlowski SW, Ilgen DR. Enhancing the effectiveness of work groups and teams. *Psychol Sci Public Interest*. 2006;7(3):77-124.
77. Schakel JK. *Organizing Distributed Knowledge for Collaborative Action: Structure, Functioning, and Emergence of Organizational Transactive Memory Systems* PhD thesis. Amsterdam, The Netherlands: Amsterdam Business School Research Institute; 2013.
78. Torres EM, Wallace DM, Zaccaro SJ, Dubrow S. Deconstructing multiteam system action: development and content validation of a multilevel multiteam system action taxonomy. *Hum Perform*. 2021;34(3):189-216.
79. Office of Inspector General. *HealthCare.Gov: Case Study of CMS Management of the Federal Marketplace*. 2016.
80. Campbell LNP, Torres EM, Zaccaro SJ, et al. Examining multiteam systems across context and type: a Historiometric analysis of failed MTS performance. *Front Psychol*. 2022;13:813624.
81. Zaccaro SJ, Marks MA, DeChurch LA. Multiteam systems: An Introduction. In: Zaccaro SJ, Marks MA, DeChurch LA, eds. *Multiteam Systems: An Organization Form for Dynamic and Complex Environments*. New York, NY: Routledge/Taylor & Francis Group; 2012:3-32.
82. Devine DJ. A review and integration of classification systems relevant to teams in organizations. *Group Dyn Theory Res Pract*. 2002;6(4):291-310.
83. Turner J, Baker R, Ali Z, Thurlow N. A new multiteam system (MTS) effectiveness model. *Systems*. 2020;8(2):12.
84. Mathieu JE, Wolfson MA, Park S. The evolution of work team research since Hawthorne. *Am Psychol*. 2018;73(4):308-321.

85. Shuffler ML, Jiménez-Rodríguez M, Kramer WS. The science of multiteam systems. *Small Group Res*. 2015;46(6):659-699.
86. Almquist ZW. Random errors in egocentric networks. *Soc Netw*. 2012;34(4):493-505.
87. An W, Schramski S. Analysis of contested reports in exchange networks based on actors' credibility. *Soc Netw*. 2015;40:25-33.
88. Bernard HR, Killworth PD. Informant accuracy in social network data II. *Hum Commun Res*. 1977;4(1):3-18.
89. Bernard HR, Killworth PD, Sailer L. Informant accuracy in social network data IV: a comparison of clique-level structure in behavioral and cognitive network data. *Soc Netw*. 1979;2(3):191-218.
90. Bernard HR, Killworth PD, Sailer L. Informant accuracy in social-network data V. An experimental attempt to predict actual communication from recall data. *Soc Sci Res*. 1982;11(1):30-66.
91. Killworth P, Bernard H. Informant accuracy in social network data. *Hum Organ*. 1976;35(3):269-286.
92. Yao N, Zhu X, Dow A, Mishra VK, Phillips A, Tu S-P. An exploratory study of networks constructed using access data from an electronic health record. *J Interprof Care*. 2018;32(6):666-673.
93. Zhu X, Tu S-P, Sewell D, et al. Measuring electronic communication networks in virtual care teams using electronic health records access-log data. *Int J Med Inform*. 2019;128:46-52.
94. Johnson RJ III. A comprehensive review of an electronic health record system soon to assume market ascendancy: EPIC®. *J Healthc Commun*. 2016;1:4. doi:10.4172/2472-1654.100036
95. Hertzum M. *Usability Testing: A Practitioner's Guide to Evaluating the User Experience*. San Rafael, CA: Springer Cham; 2022.
96. Makhni S, Zlatopolsky R, Fasihuddin F, Aponte M, Rogers J, Atreja A. Usability and learnability of RxUniverse, an Enterprise-wide app prescribing platform used in an academic tertiary care hospital. *AMIA Annu Symp Proc*. 2017;2017:1225-1232.
97. Tariman JD, Berry DL, Halpenny B, Wolpin S, Schepp K. Validation and testing of the acceptability E-scale for web-based patient-reported outcomes in cancer care. *Appl Nurs Res*. 2011;24(1):53-58.
98. Weberg D, Weberg K. Seven behaviors to advance teamwork: findings from a study of innovation leadership in a simulation center. *Nurs Adm Q*. 2014;38(3):230-237.
99. Essex R, Kennedy J, Miller D, Jameson J. A scoping review exploring the impact and negotiation of hierarchy in healthcare organisations. *Nurs Inq*. 2023;30(4):e12571.
100. Losada M. The complex dynamics of high performance teams. *Math Comput Model*. 1999;30(9):179-192.
101. Rosing K, Frese M, Bausch A. Explaining the heterogeneity of the leadership-innovation relationship: ambidextrous leadership. *Leadersh Q*. 2011;22:956-974.
102. Ernst C, Chrobot-Mason D. *Boundary Spanning Leadership: Six Practices for Solving Problems, Driving Innovation, and Transforming Organizations*. New York, NY: McGraw-Hill; 2011.
103. Ernst C, Yip J. Boundary Spanning Leadership: Tactics to Bridge Social Identity Groups in Organizations. SSRN. 2009.
104. Fick-Cooper L, Williams A, Moffatt S, Baker EL. Boundary spanning leadership: promising practices for public health. *J Public Health Manag Pract*. 2019;25(3):288-290.
105. Hunt CM, Spence M, McBride A. The role of boundary spanners in delivering collaborative care: a process evaluation. *BMC Fam Pract*. 2016;17(1):96.
106. Klein KJ, Ziegert JC, Knight AP, Xiao Y. Dynamic delegation: shared, hierarchical, and Deindividualized leadership in extreme action teams. *Adm Sci Q*. 2006;51(4):590-621.

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