Using Multimodal Digital Traces to Characterize Healthcare Team Communication Behaviors

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Background: Secure messaging and the electronic health record (EHR) are two digital tools that are regularly used in healthcare delivery. Objective: This study used multimodal behavioral data to investigate patterns of secure chat messaging use, and to determine whether those patterns are associated with patient or team outcomes. Methods: Relational event modeling (REM) was used to identify patterns of secure messaging use for each patient. REM results were investigated for associations with patient length of stay (LOS) in inpatient medicine and aggregate audit log-derived EHR time. Results: Secure message responses ("reciprocity") were common and quick. Reciprocity was associated with shorter LOS, suggesting that teams with higher message response rates may have more efficient patient throughput. In contrast, teams more likely to message a third healthcare professional after receiving a message (i.e., "turn receiving", AB-BY pattern) were associated with longer LOS, although results were not significant in sensitivity analysis. Message repetition was associated with more EHR time per day. Conclusion: While not causal, these results suggest that healthcare team secure messaging patterns are associated with patient and team outcomes. Combining multimodal data (EHR audit logs, secure messaging, clinical data) may reveal common team communication behaviors and their associations with patient and team outcomes.

Keywords: electronic health records; audit logs; chat messaging; length of stay; healthcare team processes; relational event modeling

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1. Introduction

1.1. *Background*

Healthcare professionals spend increasing amounts of time performing digital tasks[1] such as documentation, order entry, and chart review on the electronic health record (EHR), making their digital activities increasingly relevant to understanding healthcare delivery. Primary care physicians, for example, spend half of their overall clinical time on EHR-based activities[2], demonstrating that EHR tasks are an integral part of modern clinical work.

EHR audit logs, digital traces of EHR actions primarily recorded for security purposes, provide a powerful opportunity to track EHR activities.[3,4] They can be aggregated to derive measures such as team collaboration[5–7] and EHR workload[8–10]. EHR audit log-derived workload measures have been consistently associated with other measures of healthcare professionals' workload.[2,8,11] Although audit log-based measures provide a valuable approximation of digital activities, their ability to capture other foundational activities, such as team communication, is limited. Studying such behaviors requires complementary data and novel methods.

Healthcare professionals increasingly communicate through secure messaging platforms[12], allowing them to asynchronously share information, ask questions, or clarify details of patient care. Different types of secure messaging applications are now widely used across clinical settings[13], demonstrating their growing adoption. Prior work has associated messaging volume at the individual healthcare professional-level to outcomes such as decreased patient length of stay (LOS)[14], increased cognitive load,[9] and increased clinician workload.[9]

By studying multiple digital behaviors together, researchers may be able to gather a more comprehensive understanding of clinical digital activities than by studying only one dataset (audit logs or secure messaging) alone. For example, while EHR audit log data provides an ethnographic view of individual-level EHR workload, secure messaging data may allow an investigation at the team-level, as communication is inherently team-based. Clinical team measures have been extensively researched for their associations with patient outcomes; for example, fragmented and discontinuous physician care teams are associated with longer LOS[15,16], while multidisciplinary collaboration is associated with reduced in-hospital mortality[17] but inconclusive results with LOS[18,19]. Team secure messaging behaviors may similarly be associated with patient outcomes. Since healthcare communication involves multiple parties, an individual's secure messaging habits may additionally be related to their teammates' secure messaging habits and other digital behaviors. Using multimodal digital datasets can begin to reveal the complex relationships between team secure messaging, EHR workload, and patient outcomes.

1.2. *Objective*

This study aimed to investigate how patterns of team secure messaging are associated with both patient- and clinical team-based outcomes for inpatient hospitalizations, by merging multiple observational digital datasets. Identifying patterns of messages associated with relevant outcomes

may direct future research towards identifying communication inefficiencies and ultimately, improving team collaboration. The research question was: what characteristics of secure messaging interactions among clinicians are associated with patient LOS and team-based EHR workload?

2. Methods

2.1. *Study population*

All inpatient hospitalizations between January 1, 2023 and April 30, 2023 (4 months) at 12 hospitals affiliated with Washington University School of Medicine and BJC Health System were included. Adult patients (18 years or older) admitted to an inpatient medicine clinical service with a hospital LOS 3 days or longer were included. If a patient had multiple encounters meeting these criteria during the study period, only their first encounter was considered. These criteria limited heterogeneity across clinical units and excluded patients who were quickly discharged, who would likely have less variability in secure messaging use, team structure, and EHR time. Medicare's 3-day rule also informed the 3-day cutoff[20]. All hospitals in the system used the same Epic EHR (Verona, WI).

2.2. *Data*

This study incorporated multiple data sources to capture healthcare professional digital behaviors. The primary behavioral data sources were secure messaging data (model inputs) and EHR audit logs (as a secondary outcome). Additional datasets to identify inclusion criteria and covariates included admission/discharge/transfer (ADT) events, and patient characteristics such as demographics, diagnoses, and discharge disposition. All data were secondary and retrieved from Epic EHR's Clarity database.

Data analysis was conducted from November 2025 to August 2026. This study received approval under a waiver of informed consent from the Institutional Review Board of Washington University School of Medicine (IRB#202305074).

2.2.1. *Secure messaging data*

The primary data source was the secure messaging data, which included all chat conversations when the chat was linked to a patient identifier corresponding to the patients included in the study sample. Secure messaging in our health system is available through both mobile and desktop applications, and both messaging versions were included in this study. Secure messaging conversations were filtered to only those that were dyadic (i.e., excluding group messages that involved multiple healthcare professionals due to less clear response expectations to group messages). All messages associated with included conversations between the patient's admission and discharge times were included. We included messages from and to all healthcare professional roles because this study was exploratory and we did not have role-specific hypotheses; rather, we wanted to measure messaging patterns across the entire care team. Relevant data elements that were retrieved included the conversation ID, patient ID, sender ID, receiver ID, and timestamp. Sender and receiver IDs

were included regardless of the user's clinical role (e.g. nurse, physician, administrative support, technician, etc) or setting (inpatient or outpatient).

2.2.2. *EHR audit logs*

EHR audit logs were extracted from the access logs table (ACCESS_LOG) in the Epic Clarity database. Audit logs included the action description, timestamp, patient ID, encounter ID, healthcare professional ID, healthcare professional role, and action ID. Audit logs were extracted for all healthcare professionals that interacted with eligible patients' EHR between admit and discharge.

2.2.3. *Admission, discharge, and transfer events*

The ADT events were used to identify hospitalizations admitted to a medicine service. Patients could be admitted through emergency medicine, adult emergency medicine, or pediatric emergency medicine specialties so long as they were transferred to a hospitalist or medical specialty in any of the hospitals affiliated with the health system.

2.2.4. *Patient characteristics*

Demographic information for patients seen in eligible hospitalizations was captured, including documented patient sex, race, age, and insurance status. All billing ICD-10 diagnoses associated with the encounter were recorded. Diagnosis-related groups (DRGs) represented the primary billed reason for hospitalization.

2.3. *Measures*

2.3.1. *Length of stay in hours (outcome)*

The primary outcome was patient LOS, calculated as the time difference between admission and discharge times, in hours. LOS is reported as median and interquartile range [Q1, Q3].

2.3.2. *EHR time per day in minutes (outcome)*

Total time on the EHR was used as a proxy for EHR workload, similar to prior research[21,22]. For each healthcare professional interacting with each patient's chart, the time delta between subsequent EHR audit log actions was calculated and summed across all actions to determine total EHR time. Any time deltas greater than 5 minutes were removed, representing a 5-minute timeout period of inactivity, as has been used in previous research[10,23,24]. Total EHR time for all healthcare professionals for each patient were aggregated to represent the total EHR time across the entire encounter (in minutes). EHR time was divided by the patient's LOS (in hours) so that the variable is an estimate of relative EHR workload rather than primarily an artifact of the patient's LOS.

2.3.3. *Covariates*

Additional covariates included patient demographics of age, sex (male, female), race (White, Black or African American, or other), and insurance (Medicare, Medicaid, Managed Care, Commercial,

Worker's Comp, Multiple insurance types, or missing). Clinical characteristics controlled for treatment setting and patient clinical complexity, which were hypothesized to be related with clinical workload; treatment setting variables included the hospital name and a binary indicator of whether they spent any time in the intensive care unit (ICU). Clinical complexity was operationalized as the DRG and unweighted Elixhauser comorbidity score. All billed ICD-10 codes were aggregated into an unweighted Elixhauser comorbidity score[25], which counts the chronic co-occurring conditions billed out of a list of 38 conditions, and represents overall sickness.

2.4. *Data pre-processing*

Age, Elixhauser score, messaging volume, and care team size were coded as continuous variables. Log transformation was used for LOS, EHR time per day, care team size, and messaging volume, which were all right-skewed. All other variables were categorical with the majority group used as the reference group (ref; White race, Medicare insurance, female sex, no ICU).

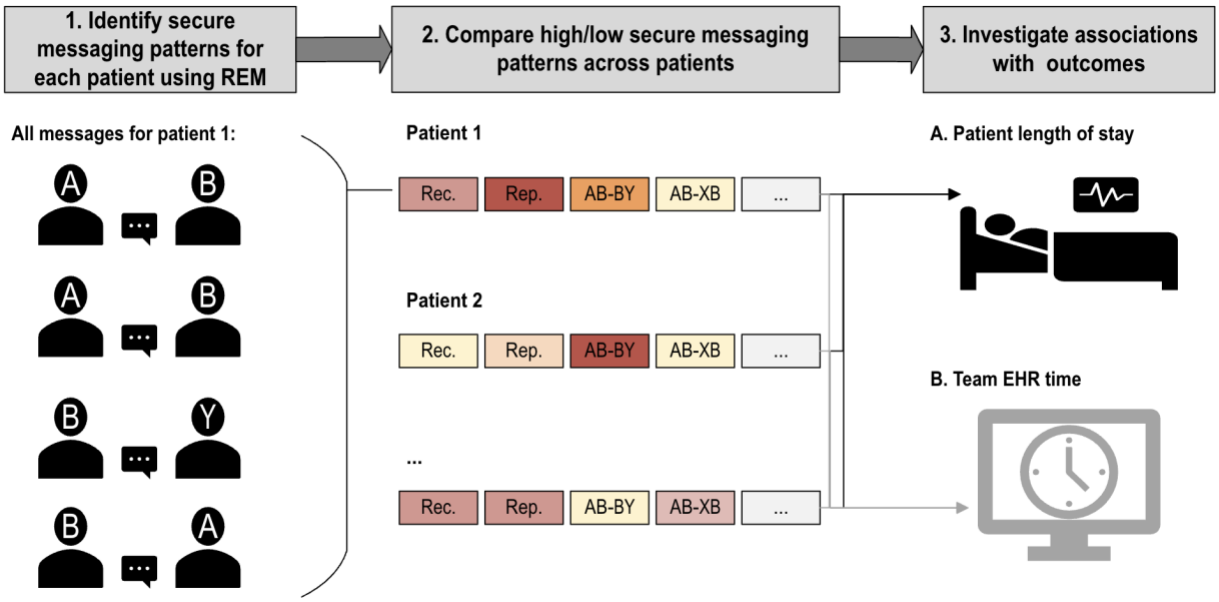


Fig. 1. Methodology to identify secure messaging patterns associations with patient and team outcomes. For each patient, we measured secure messaging patterns of: reciprocity (Rec), repetition (Rep), and four turn-switching behaviors (AB-BY, AB-XB, AB-AY, AB-XA). We investigated associations of each standardized term with outcomes of LOS and EHR time.

2.5. *Statistical Approach*

The analysis followed three steps (**Figure 1**). First, relational event modeling (REM) was used to identify patterns in secure messaging use at the patient-level. Second, REM estimates were standardized across all patients to derive how messaging patterns compared to the average. Finally, these standardized terms were investigated for associations with the outcomes using mixed effects linear regression. Details on each step are below and in **Figure 1**.

2.5.1. *Relational event modeling*

Our analytical approach applied REM to identify patterns of secure messaging for each patient (**Figure 1- Step 1**). A growing body of literature in social science has used relational events or similar frameworks to analyze timestamped networked communicative events in various settings[26–29]. REMs identify patterns of communication by user attribute, dyadic attributes, team attributes, or participation switching. REMs fit a set of survival models to identify the rate of certain communication patterns occurring. They consistently reveal well-understood social network patterns such as reciprocity, triadic closure, and more in varied communication settings[26–29].

Table 1. relational event model participation shift patterns

Term	Definition
REM intercept	baseline "hazard" to message, beyond all specified messaging patterns
Reciprocity	likelihood for any person "A" to message person "B", given the recency that "B" has messaged person "A".
Repetition	likelihood for any person "A" to message person "B", given the recency that "A" has messaged person "B".
Turn continuing (AB-AY)	likelihood that the sender, "A", of a given message will be the sender to a third person, "Y", in the very next event.
Turn receiving (AB-BY)	likelihood that the receiver, "B", of a given message will be the sender to a third person, "Y", in the very next event.
Turn usurping (AB-XA)	likelihood that the sender, "A", will be the receiver of the next message by someone who they did not just message.
Turn usurping (AB-XB)	likelihood that the receiver, "B", will be the receiver of two subsequent messages from two different senders.

An REM was fit for each patient separately to identify their team's messaging patterns. The REM effects included an intercept for baseline messaging hazard, repetition, reciprocity, and participation shifts for turn switching[30]. Definitions of each pattern are summarized in **Table 1**.

We exponentiated effect estimates to calculate the hazard ratio (HR), which represents the rate of each pattern occurring relative to all other patterns, as has been done in other research[29]. For instance, a higher reciprocity HR means the patient's healthcare team responded at a higher rate (more frequently and/or more rapidly). HRs are interpreted relative to a null of 1: a pattern with HR greater than 1 occurred at a greater rate, while a pattern with HR less than 1 occurred at a lower rate. Estimates were capped at the largest value the computer could store – exp(709) – where predictive power was near-perfect and exponentiated HR became too large. Results are reported as median, quartile 1 (Q1) and quartile 3 (Q3).

2.5.2. *Standardization*

The resulting (un-exponentiated) REM effect estimates (intercept, repetition, reciprocity, four participation shifts) were standardized across all patients in the cohort. This transformed each estimate to have a mean of zero and a standard deviation of one ("z-score"), allowing us to assess how a patient's team's secure messaging habits differ from the rest (**Figure 1-Step 2**). Patients with a positive z-score have "high" reciprocity, for example, if their team's secure messaging patterns revealed higher-than-average rate of response. They have "low" repetition, for example, if their

team's secure messaging patterns revealed a negative standardized repetition term, indicating a lower-than-average rate of messaging the same recipient repeatedly.

2.5.3. *Mixed effects linear regression*

Finally, two linear regressions investigated the association of messaging patterns with dependent variables of LOS (hours) and EHR time per day (minutes; **Figure 1-Step 3**). The independent variables were the standardized REM estimates (repetition, reciprocity, participation shifts). Covariate fixed effects included demographics (race, sex, age, insurance) and clinical variables (ICU and Elixhauser comorbidity score). Random effects included the hospital at which the patient was treated and their DRG. Results are reported as beta coefficients and 95% confidence intervals (CI).

2.5.4. *Sensitivity analysis*

Several secondary analyses investigated robustness of the results to model specification. Results are presented as stepwise analyses (models 1-4) to demonstrate how effect estimates change with the inclusion of subsequent terms. First, models included only reciprocity, repetition, and REM intercept (model 1), then added the four participation shifts (model 2). Then, models were modified to include fixed effects for the messaging volume (number of messages, model 3) and care team size (number of unique secure messaging users, model 4). This analysis was intended to investigate whether associations between REM patterns and outcomes were explainable by messaging volume and care team size, or if the micro-patterns of messaging, independent of volume and care team size, explain the relationships. Second, the patient cohort was filtered to only those with at least three unique secure messaging users, since teams with only two users will not demonstrate any participation shifting behaviors from which the model can learn. Although REMs have been proven to produce reliable explanatory estimates even with small risk sets[31], this sensitivity analysis reduced the uncertainty of REM estimates by filtering to patients with more data on which to train.

2.5.5. *Software*

Audit log, secure messaging, and ADT data preprocessing was done using Python version 3.10.6. Statistical analysis was done using R version 4.4.0 and packages relevent[32] for REM, lme4[33] and lmerTest[34] for mixed-effects linear models, and sjPlot[35] for summary tables.

3. Results

3.1. *Summary statistics*

6,737 hospitalizations met inclusion criteria and had at least one dyadic secure message during their encounter, which constituted our final analytic sample. Patients had a median LOS of 136 [Q1 96.6, Q3 202] hours and median EHR time per day of 327 [272, 400] minutes. The median secure messages per patient during their hospitalization was 29 [14, 60] messages across 8 [4, 14] conversations and a care team of size 10 [6, 16] healthcare professionals involved in messaging. 3,643 (54.1%) patients were female, 4,276 (63.5%) were White, 4,468 (66.3%) had Medicare insurance, and the median age was 67 [56, 78] years. 856 patients (12.7%) had any amount of time

in the ICU during their hospitalization and median Elixhauser score was 5 [4, 7]. The most common DRGs were "septicemia or severe sepsis without MV >96 hours with major complication and comorbidity (MCC)" (n=509, 7.6%), "heart failure and shock with MCC" (n=365, 5.4%), and "respiratory infections and inflammations with MCC" (n=243, 3.6%).

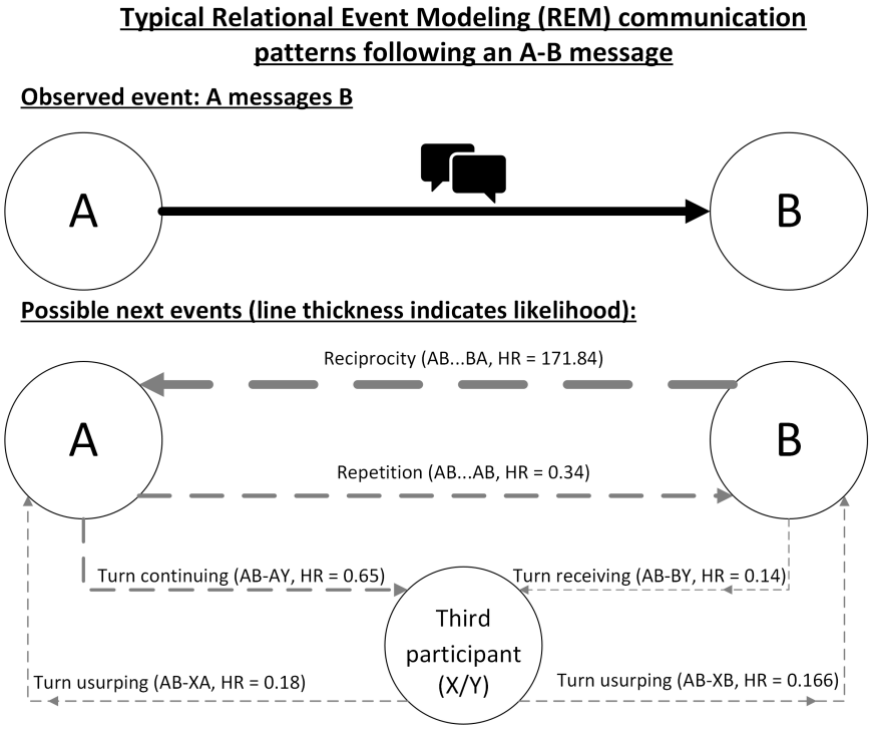


Fig. 2. Possible participation shifts after an observed A-B message (solid black line), where rate of unobserved events (dashed grey lines) is indicated by line thickness and median hazard ratios (HR).

3.2. *REM model descriptive statistics*

On average, patients' care teams were highly likely to message those who had messaged them (**Figure 2**; reciprocity median HR=171.84, Q1=21.95, Q3=3664.93). A secure messaging user was 171 times more likely to respond to a person who had recently messaged them than they were to message a different person. Care teams were less likely to message those they had already messaged (repetition, median HR=0.34, Q1=0.011, Q3=1.53). Of participation shift patterns, turn continuing (AB-AY) was most likely (median HR = 0.65, Q1=<0.00001, Q3=2.04). Both turn usurping patterns were similarly likely (AB-XB median HR=0.166, Q1=<0.00001, Q3=0.98; AB-XA median HR=0.18, Q1=<0.00001, Q3=0.92). Turn receiving (AB-BY) was least likely (median HR=0.14, Q1=<0.00001, Q3=1.69).

3.3. *Associations of REM model estimates with LOS*

Reciprocity was robustly associated with shorter LOS and turn receiving (AB-BY) was robustly associated with longer LOS. In other words, a one-standard-deviation increase in a patient's care team's reciprocity was associated with a 3% shorter LOS (exp(-0.02894) - 1; **Table 2, column 2**:

estimate = -0.02894, CI=-0.04805, -0.00983). A one-standard-deviation increase in turn receiving was associated with a 5% longer LOS (exp(0.04262)-1; **Table 2, column 2**: estimate = 0.04262, CI=0.02320, 0.06203). Repetition, turn continuing, and turn usurping (AB-XB) were associated with longer LOS (**Table 2, column 2**) but the association was no longer significant after controlling for care team size or messaging volume (**Table 2, columns 3-4**).

Table 2. Association between secure messaging patterns and log-LOS: results of multiple stepwise model specifications

Predictor	1. Reciprocity + repetition	2. + participation shifts	3. + messaging volume	4. + care team size
REM intercept	**0.04836**	**-0.02526**	**-0.04949**	**-0.02507**
	(0.03620, 0.06051)	**(-0.04376, -0.00675)**	**(-0.06634, -0.03263)**	**(-0.04111, -0.00903)**
Reciprocity	**-0.03931**	**-0.02894**	**-0.02054**	**-0.01835**
	(-0.06142, -0.01719)	**(-0.04805, -0.00983)**	**(-0.03791, -0.00318)**	**(-0.03491, -0.00179)**
Repetition	**0.04338**	**0.04530**	-0.00024	-0.01294
	(0.02105, 0.06572)	**(0.02564, 0.06497)**	(-0.01826, 0.01777)	(-0.03015, 0.00426)
Turn continuing		**0.02256**	0.01390	0.00070
(AB-AY)		**(0.00324, 0.04188)**	(-0.00366, 0.03145)	(-0.01606, 0.01746)
Turn receiving		**0.04262**	**0.01944**	**0.02077**
(AB-BY)		**(0.02320, 0.06203)**	**(0.00178, 0.03711)**	**(0.00394, 0.03760)**
Turn usurping		0.01323	-0.00175	0.00332
(AB-XA)		(-0.00709, 0.03356)	(-0.02023, 0.01672)	(-0.01429, 0.02093)
Turn usurping		**0.02080**	0.01099	0.00806
(AB-XB)		**(0.00095, 0.04064)**	(-0.00704, 0.02903)	(-0.00915, 0.02526)
Messaging volume			**0.23824**	
			(0.22607, 0.25040)	
Care team size				**0.41992**
				(0.40289, 0.43696)

Significant findings at a significance level of 0.05 are indicated in bold in the table. Covariates that remain significant across all models are indicated by "Sig" in this legend. All models additionally adjusted for sex, race, insurance, age, Elixhauser (Sig), and ICU (Sig). Random effects were included for hospital and DRG.

3.4. *Associations of REM model estimates with team EHR time*

Repetition was associated with less EHR time. In other words, a one-standard deviation increase in repetition was associated with a 1% increase in EHR time per day (exp(0.01099) – 1, **Table 3, column 2**: estimate = 0.01099, CI=0.00106, 0.02091). This suggests that patient care teams who were more likely to repeatedly message the same people had higher EHR time, but the association is at least partially explained by higher overall messaging volume. No other participation shifts were consistently associated with EHR time (**Table 3, columns 2-4**).

3.5. *Sensitivity analysis*

When including fixed effects for messaging volume and care team size, some communication patterns remain significantly associated with LOS and EHR time. Reciprocity remains significantly associated with shorter LOS when controlling for messaging volume (**Table 2, column 3**), and care team size (**Table 2, column 4**). Similarly, turn receiving remains significantly associated with

longer LOS when controlling for messaging volume (**Table 2, column 3**) and care team size (**Table 2, column 4**). Repetition's association with EHR time per day is marginally significant ($p<0.1$) when controlling for care team size (**Table 3, column 4**), but is not significant when controlling for messaging volume (**Table 3, column 3**).

Table 3. Association between secure messaging patterns and log-EHR time per day: results of multiple stepwise model specifications

Predictor	1. Reciprocity + repetition	2. + participation shifts	3. + messaging volume	4. + care team size
REM intercept	**0.01553**	0.00776	0.00558	0.00775
	(0.00942, 0.02163)	(-0.00159, 0.01711)	(-0.00378, 0.01493)	(-0.00160, 0.01710)
Reciprocity	**-0.01116**	-0.00834	-0.00763	-0.00815
	(-0.02226, -0.00006)	(-0.01799, 0.00130)	(-0.01725, 0.00200)	(-0.01780, 0.00150)
Repetition	**0.01218**	**0.01099**	0.00696	0.00987
	(0.00096, 0.02340)	**(0.00106, 0.02091)**	(-0.00302, 0.01695)	(-0.00015, 0.01989)
Turn continuing		-0.00079	-0.00156	-0.00122
(AB-AY)		(-0.01054, 0.00895)	(-0.01129, 0.00817)	(-0.01098, 0.00854)
Turn receiving		0.00748	0.00536	0.00704
(AB-BY)		(-0.00230, 0.01726)	(-0.00442, 0.01513)	(-0.00275, 0.01683)
Turn usurping		0.00275	0.00135	0.00254
(AB-XA)		(-0.00750, 0.01301)	(-0.00889, 0.01159)	(-0.00772, 0.01280)
Turn usurping		-0.00047	-0.00128	-0.00070
(AB-XB)		(-0.01049, 0.00955)	(-0.01128, 0.00872)	(-0.01072. 0.00932)
Messaging volume			**0.02119**	
			(0.01445, 0.02793)	
Care team size				0.00809
				(-0.00181, 0.01799)

Significant findings at a significance level of 0.05 are indicated in bold in the table. Covariates that remain significant across all models are indicated by "Sig" in this legend. All models additionally adjusted for sex, race (Sig), insurance (Sig), age (Sig), Elixhauser (Sig), and ICU (Sig). Random effects were included for hospital and DRG.

When filtering the dataset to only patients with care team size greater than or equal to three, the results are in the same direction for both outcomes, but not consistently significant. N=6,359 (94%) patients had a messaging care team of at least three. Reciprocity's association with LOS is significant for two step-wise models (model 1: estimate = 0.04403, CI =0.02142, 0.06665); model 2: 0.0342, CI=0.01486, 0.05355); it is marginally significant ($p<0.1$) when including messaging volume (model 3: -0.01035, CI=-0.02793, 0.00723) or care team size (model 4: -0.01654, CI=-0.03316, 0.00009). Similarly, turn receiving is significantly associated with longer LOS for the base model (model 2: 0.04986, CI=0.03002, 0.06970) but is not significant after controlling for messaging volume (model 3: 0.00582, CI=-0.01219, 0.02384) nor when controlling for care team size (model 4: 0.00606, CI=-0.01094, 0.02307). Repetition's association with EHR time is significant and positive (model 1: 0.01157, CI=0.00025, 0.02289) but no longer significant when controlling for participation shifts (model 2: 0.008, CI=-0.00175, 0.01776), messaging volume (model 3: 0.00522, CI=-0.00460, 0.01504), or care team size (model 4: 0. 0.00853, CI=-0.00129, 0.01835).

4. Discussion

This study used multimodal data consisting of secure messaging metadata, EHR audit logs, and clinical data to ascertain the association between hospital team communication and both patient and team outcomes. There were four main findings: 1) secure messages were consistently responded to in inpatient medicine (high reciprocity). 2) Reciprocity was associated with shorter patient LOS, suggesting that care teams that consistently responded to messages may have more efficient patient throughput. 3) In contrast, messaging repetition was associated with more patient care-related EHR time per day (for the team), which may represent complexity of patient care or needing to "nudge" the recipient for responses. 4) Meanwhile, care teams that were more likely than average to follow turn receiving patterns were associated with longer LOS. This may suggest that teams whose message recipient involves a third person in communication represent task dependencies, or that complex information is communicated over text-based messages. Patterns of repetition and all four turn switching behaviors vary widely across patients, as demonstrated by the CIs crossing 1. These results can inform future research on the directionality of efficient team communication: studying the dynamics of reciprocity, repetition, and turn receiving in medical settings may enable more efficient patient throughput and reduce unnecessary workload. Alternatively, it may reveal that certain messaging patterns are not the cause of high LOS and high workload, but they are effects of patient care. This could enable better resource allocation if hospital systems can anticipate that certain patients will require more intensive communication and EHR workload needs.

4.1. *Implications*

The finding that reciprocity was the most likely communication pattern is intuitive and consistent with previous research that shows secure messages have a short time-to response (median=2.4 minutes), with most conversations including at least one response[36]. In many communication settings, it is both required and a social norm to respond to those who communicate with you. However, it is important to note that the reciprocity hazard may overrepresent the likelihood of a response[37]; the results should be interpreted for their direction and not for their magnitude. Nonetheless, reciprocity is the most likely pattern of secure use messaging, representing a strong propensity for secure messaging users to respond to messages they receive. In contrast, healthcare professionals were less likely to message the same person again than to message another person. This represents that secure messaging communication networks were distributed across teams for the typical patient, rather than confined to dyadic communication. Overall, team secure messaging use patterns appear to matter more for efficiency (as measured by patient LOS) than for workload (as measured by EHR time), given that multiple patterns are associated with LOS.

Further, the importance of reciprocity to LOS has potential implications for communication efficiency in clinical coordination. Higher secure messaging reciprocity was associated with shorter LOS. This suggests that teams who more consistently and quickly respond to secure messages treat patients who are discharged quicker. One possible explanation is that high reciprocity represents better visibility into action progress (through a response or confirmation of completed actions), which in turn may enable better coordination. Interestingly, this relationship was still significant in the base model (model 2) when filtering to teams of at least three users, but only marginally

significant after both filtering and controlling for team size or messaging volume. This suggests that the relationship with LOS was partially driven by patients with small care teams (only two people messaging), whose reciprocity was smaller and who had short LOS. When excluding these patients, the remaining relationship with LOS is primarily explained by messaging volume and/or by care team size, although reciprocity remains nearly significant. Reciprocal communication may contribute to more efficient clinical workflows and positively impact patient outcomes, but more work is needed on ways to differentiate messaging volume and care team size from reciprocity.

On the other hand, repetition of secure messages was associated with higher entire-team EHR time, which is a proxy for EHR workload. This may represent healthcare professionals needing to follow-up or "nudge" message recipients to gather information. Rather than being a causal relationship, it may represent that more clinically complex patients require both additional clarification through repeated messaging and require more EHR workload to read prior notes, manage comorbidities, or document care. The relationship between higher patient complexity and greater EHR workload has been demonstrated in prior studies[8]. Alternatively, if the recipient is extremely busy managing the patient's care (with high EHR workload), a second secure message may be necessary to remind them to respond during periods of high cognitive burden. Multiple messages sent sequentially to communicate the same idea would contribute to the repetition terms in these models. Without message content, it is difficult to say with certainty whether two messages are a meaningful repetition, or if they are due to sender messaging preference. Nonetheless, the results suggest that this pattern is associated with team workload, thus the pattern may be interruptive even if repeated messages communicate the same thought.

Beyond dyadic patterns, turn receiving (AB-BY) was associated with LOS. This pattern represents a specific kind of coordination where someone who is asked a question or requested to perform an action must first get clarification from another person. This pattern is associated with longer LOS. It is possible that this is due to delayed dependencies: for example, if a nurse messages a physician to ask about a symptom a patient is experiencing, and the physician must message another physician (perhaps the patient's primary care doctor) before they prescribe a medication, there may be delays between each interaction. These delays could prolong the patient's overall LOS if severity of condition worsens or if required care is delayed while waiting. Alternatively, these relationships could represent secure messaging requests which require clarification, and act as a proxy for more complex patient care. However, turn receiving is no longer associated with LOS in the filtered sensitivity analysis when controlling for team size or messaging volume. Turn receiving cannot be observed in teams of two; nonetheless, these patients had higher average AB-BY values representing higher likelihood of this pattern occurring (potentially due to less training data). Patients with small care teams additionally had a lower average LOS, which contributed to the overall relationship. Although exploratory, these results may suggest team coordination in two-person care teams is substantially different from coordination in larger care teams. More work is needed to understand the nature of these differences.

Methodologically, this analysis makes possible an ethnographic study of healthcare professional communication patterns and how they relate to important patient and health system outcomes. Other studies could apply these methods to specific healthcare specialties or patient populations to understand conversational patterns in those settings.

4.2. *Limitations*

These results should be interpreted in the context of a few important limitations. First, we did not have data on the content of these secure messages. While reciprocity may indicate a "response" to a message, it cannot conclusively be determined that the reciprocal message pattern indicated a response to the same topic. Message length or topic may contribute differentially to the association with LOS or EHR workload, and natural language processing of message content would help with understanding differences in the complexity or urgency of messages. Second, this was a single site, single specialty study, limiting generalizability of results. Third, there may be residual confounding; for example, specific inpatient medicine units who work more closely face-to-face may use secure messaging less, and also treat patients who have different clinical presentations, leading to inherent differences in LOS. We attempted to control for this by limiting the setting to one specialty only, controlling for Elixhauser comorbidity, and using random effects for hospitals and DRGs; however, some unit-level, team-level, or severity-level variation may remain. Finally, some results were no longer significant in sensitivity analysis after filtering to patients with larger care teams, and results changed slightly when controlling for care team size or messaging volume. Additional analysis is needed to better understand these patients with smaller care teams and how they may contribute to the overall relationships between reciprocity, turn receiving, repetition, and both outcomes.

4.3. *Future work*

Future work could include only healthcare professionals determined to be in the patient's core care team, as defined by a previously validated algorithm[38], to investigate whether the messaging patterns differed within the primary care team versus the wider team of collaborating healthcare professionals. It could alternatively assess EHR workload changes for only these individuals, or for the individuals involved in messaging. Replicating these results in other healthcare systems, settings, and specialties would reveal whether secure messaging patterns are local or shared across many clinical settings. As mentioned above, additional analysis into REM accuracy for patients who have few messages or smaller care teams would help answer an open question in REM research as to the minimum required risk set for reliable REM estimates. Finally, future work could explore interaction terms between healthcare roles and patterns of secure chat messages to investigate whether communication patterns, and their associations with outcomes, differ by professional role (e.g. nurse, physician).

4.4. *Conclusion*

This study used multimodal observational datasets to derive patterns of team digital communication. Secure messaging logs and EHR audit logs capture communication and clinical workload attributes that otherwise could not be measured at-scale. Moreover, measuring them together in a multimodal analysis enables researchers to understand how two common digital activities are related and reflect clinical behaviors. These messaging behaviors were associated with both patient (LOS) and team (EHR workload) outcomes, demonstrating the importance of measuring secure messaging use patterns at the team-level and providing insight into care coordination efficiency.

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