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Supplementary Materials for How Digital and Physical Care Team Interaction Affect Processing Times: A Case Study of Hospitalists

Materials—Data

The data was assembled from two sources: a time-motion study and Electronic Health Records (EHR) at Northwestern Memorial Hospital (NMH) in Chicago. The time-motion study was performed by us closely observing and recording every single activity of one hospitalist during each observation day. Each hospitalist works for 7 consecutive days and is off work for the next 7 days. On each day of our observational study we selected one hospitalist for observation based on the staffing schedule (there are about 10 hospitalists scheduled per day at NMH). We shad- owed the selected hospitalist from 7 a.m. to the end of his or her shift on that day (varies from 2 p.m. to 8 p.m.) and logged all hospitalist' activities, second by second, using the EternityQR app on iPad. The data contains information of each activity about: 1) activity date, start and end time (accurate to seconds); 2) activity category (review chart, visit patient, document progress note, make/receive a phone call, send/receive a page, face-to-face conversation, meeting); 3) the identifier of the patient concerned; 4) the identifier of the care provider the hospitalist commu- nicated with if the activity was a communication; 5) other details (e.g., the textual page content "Patient F needs NPO?"1). Table S1 illustrates a snapshot of this data source.

The second data source was extracted from the hospital's EHR. For each patient identifier in the time-motion study, we retrieve all his or her medical records that include: 1) patient admission and discharge date and time; 2) patient information—demographics (age, gender, race), acuity level (1 to 5 indicating low to high acuity), Intensive Care Unit (ICU) status (1 if the patient ever stays in the ICU during his hospitalization); 3) details of all documented activities regarding the patient throughout his or her hospitalization stay (progress notes, med- ical/administrative orders and forms)—documentation time, the identifier and title of the care provider who input the documentation.

Methods

Variable definition and measurement

The unit of analysis is (patient, day): each data vector concerns a specific patient on a specific observed day. We define dependent and independent variables by merging the two data sources and aggregating from the hospitalist activity level (illustrated in Table S1) to the (patient, day) level. The dependent variables processing time and communication time, and the independent variables X = (P, W, T) are defined as follows:

Case time		**Activity**	**Start time**	**End**	**Remark**
Day	**Patient**				
1	A	Review chart	6:45:19	6:58:57	
1	B	Review chart	6:58:58	6:13:17	
1	-	-	-	-	
1	-	-	-	-	
1	-	-	-	-	
1	A	Visit patient	9:26:58	9:31:46	
1	B	Visit patient	9:31:47	9:55:41	
1	-	-	-	-	
1	-	-	-	-	
1	-	-	-	-	
1	A	Document progress note	11:22:22	11:23:56	
1	F	Receive page	11:23:57	11:24:13	*Nurse 001[1] : "Patient F needs*
1	A	Document pro- gress note	11:24:14	11:30:10	
1	F	Make phone call[2]	11:30:11	11:32:12	*Respond to the nurse 001*
1	F	Send page	11:32:13	11:32:30	*To the PCP 002 of patient F*

Case time		Activity	Start time	End	Remark
Day	Patient				
1	A	Document progress note	11:32:31	11:34:35	
1	A	Send page[3]	11:34:36	11:36:20	Reach out to the cardiology team
1	B	Document progress note	11:36:21	11:38:00	
1	G	Receive phone call	11:38:01 schedule	11:39:10	Lab specialist 003 confirms a test
1	G	Document progress note	11:39:11	11:39:54	
1	-	-	-	-	
1	-	-	-	-	
1	-	-	-	-	
1	H	Document progress note	14:31:04	14:32:13	
1	F	Receive phone call	14:32:14	11:36:19	The PCP 002 called to respond the previous request
1	-	-	-	-	
1	-	-	-	-	
1	-	-	-	-	

[1]Nurse 001 is included in the hospitalist's physical team of patient F on day 1 since she was observed communicating with the hospitalist regarding patient F on this day.
[2]This phone call was made to respond to an external interruption from the nurse and led the hospitalist switch from documenting patient A's progress note to a communication activity, thus creating one more task switch to respond for patient A on day 1.
[3]This text page was sent to reach out to a care provider by the hospitalist when he felt needed regarding patient
A 's note documentation, thus creating one more task switch to reach out for patient A on day 1.

Table S1: A snapshot of data collected from the time-motion study

Dependent variables: The first dependent variable—(patient, day) processing time—is the sum of all observed hospitalist-activity-times for that specific patient on that specific day of observation. The second dependent variable—(patient, day) communication time—is the total time the hospitalist spends on interpersonal communications (phone conversations or face-to- face meetings) with other care providers about the specific patient on the specific day. Both processing time and communication time are calculated from activities observed from the time- motion study. (Note that this information cannot be extracted from the EHR as many of these activities are not recorded in the EHR).

Independent variables:

Patient, P. We code the patient characteristics with both data sources: Acuity level and Intensive Care Unit (ICU) indicator are directly retrieved from the EHR. Length of Stay (LOS) is measured by the difference in hours between the patient's admission and discharge date/time that are available in the EHR. The above three variables reflect patient health severity. In addi- tion, we define PCP-NMH-employment indicating whether the patient's Primary Care Physician (PCP) is employed by NMH (1=Yes, 0=No)—available in the care provider information in the EHR, Discharge today indicating whether the patient is being discharged on that day (1=Yes, 0=No)—obtained from the patient discharge date in the EHR, and Patient-Hospitalist familiar- ity calculated by the number of days the patient was seen by the hospitalist observed on that day. We also capture the Time of day when the hospitalist starts document the patient EHR and Number of other patient EHRs in pipeline (calculated by the number of patient files that the hospitalist has opened for documentation but has not yet finished upon starting the focal patient EHR documentation)—both are retrieved from the time-motion study.

Workflow, W. We identify the hospitalist in charge for each (patient, day) and capture the number of task switches the hospitalist made while documenting the patient EHR. In particular, we distinguish the task switches initiated by the hospitalist herself to reach out to other care providers, from switches to respond to other people's communication requests. These variables are calculated from the time-motion study (See example in Table S1).

Team, T. We tag a care provider as belonging to a hospitalist's physical team on a given (patient, day) if the provider interacted with the hospitalist via interpersonal communications regarding the patient (observed in the time-motion study), and to the patient's digital team if the provider entered data in the patient's EHR file.

We establish a team evolution model by decomposing the physical team and the digital team on each day into three membership categories: cumulative members, daily members and new members. For a (patient, day) pair, cumulative members include all care providers who have performed at least one activity on the patient prior to the beginning of this day. Daily members refer to people who perform at least one activity on the patient on this day, while new members are those that perform at least one activity on the patient on this day yet have not performed any activity on the patient prior to that day; see Figure S1. Thus,

A physical (or digital) cumulative team at the end of day *t*
= Cumulative physical (or digital) members at the beginning of day *t*
+ New physical (or digital) members during day *t*

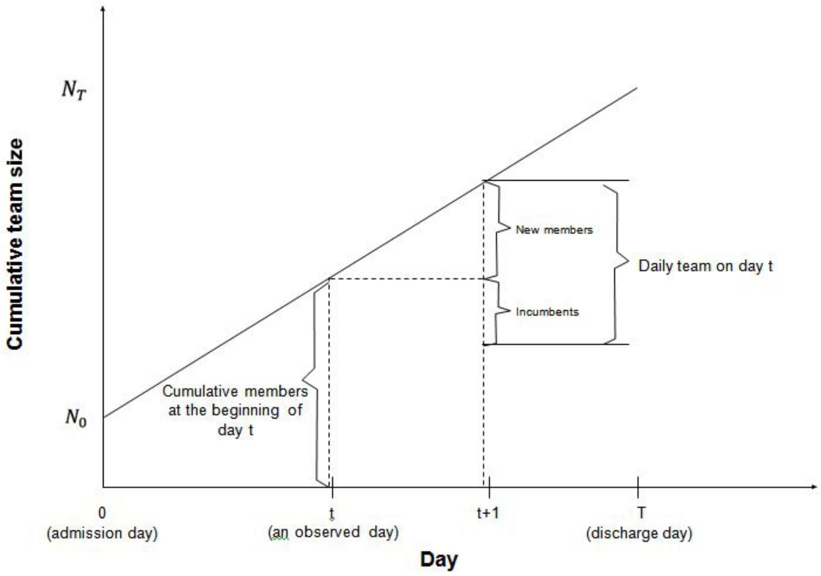

Figure S1: Daily team evolution. On any day t, a (physical or digital) team consists of cumulative members—who have performed at least one activity relating to the specific patient prior to the beginning of day t—and daily team members—who perform at least one patient activity on day t. The subset of daily team members called "new members" have day t as their first time performing any activity relating to the patient

We define team size and stability variables via these three membership categories for physical and digital teams, respectively: cumulative team size, daily team size and new member fraction (calculated $\frac{\text{New Memeber Team Size}}{\text{Daily team size}}$. The calculations of these variables for digital and physical teams for each (patient, day) are separately performed with the original EHR data and the time-motion data before data merging. Since EHR data covers longer time span (each patient's entire inpatient stay) than the time-motion data,

Collaboration experience proxies for team member familiarity, specifically the familiarity between the hospitalist and another team member. The hospitalist collaboration experience with a specific caregiver *j* on observation day *t* is calculated by the number of digital teams extracted from the EHR to which both *j* and the specific hospitalist belonged in the month leading up to day *t*. The collaboration experience on day *t* is then obtained by averaging over experiences with all team members *j* on day *t*.

Statistical Analysis

Factor analysis

Factor analysis decomposes a covariate matrix *C* into linear combinations of uncorrelated factors **U**, that satisfy *C* = **BU** and *COV* **(U)** = **I**, where **B** is the factor loading matrix. The resulting grouping result is called as orthogonal rotated factor pattern due to the orthogonality requirement of *COV* **(U)**. According to the grouping method in (2), whether an original covariate belongs to a certain factor is determined by whether the magnitude of its factor loading exceeds certain cutoff point[2].

With covariates **X = (P, W, T)** defined in section 2.1, we follow the procedures developed by (2)[3]:

1. We group the patient characteristics into factors **F** such that **P** = **LF**, subject to *COV* **(F)** = **I**, where **L** is the loading factor matrix. To ensure robustness, we alter the constraint on number of factors from 2 to 3—the grouping results are shown in Table S2;

2. We group the hospitalist and team characteristics into factors **G** such that **[W,T]** = **MG**, subject to *COV* **(G)** = **I**, where **M** is the loading factor matrix. Under different constraints on number of factors (3 and 4), the grouping results are shown in Table S2.

We also performed a factor analysis on the entire variable set instead of separately grouping patient characteristics and team variables. The predicted processing times are robust. The separated grouping method has the advantage of easier interpretation of factors in terms of original variables.

Variable	Factor loading	
(a) Team and Hospitalist workflow characteristics	**3 Factors**	**4 Factors**
	Factor 1	*Factor 1*
Digital cumulative team size	1.0	1.0
Digital new-member fraction	-0.8	-0.7
Physical cumulative team size	0.7	0.6
	Factor 2	*Factor 2*
# of switches to reach out	0.8	0.8
# of switches to respond	0.6	0.6
Physical daily team size	0.7	0.7
	Factor 3	*Factor 3*
Digital daily team size	0.7	1.0
Physical new-member fraction	0.4	0.9
		Factor 4
Collaboration experience	-0.4	-0.4
Factor analysis statistics		
***p*–value**[1]	0.1	0.8
(b) Patient characteristics	**2 Factors**	**3 Factors**
	Factor 1	*Factor 1*
Discharge today?	-0.4	-0.4
Length of Stay	0.9	0.9
ICU indicator	0.5	0.5
	Factor 2	*Factor 2*
# of days seen by the hospitalist	1.0	1.0
		Factor 3
Time of day the focal patient EHR starts being documented	1.0	
Acuity level		
PCP employed by NMH?		
Factor analysis statistics		
p–value[1]	0.1	0.2

[1]*The null hypothesis is that the number of factors constrained is sufficient*

Table S2: Orthogonal rotated factor pattern (|Loadings| >= 0.4) under different factoring constraints. The grouping result is consistent across different constraints on number of factors: 3 and 4 factors on team-workflow variables, and 2 and 3 factors on patient characteristics. The only difference is that collaboration experience is left out from Factor 3 and grouped as a new Factor 4. As to patient characteristics, Time of day the focal patient EHR starts being documented needs to be included in the analysis since it is grouped as the third factor

Regression

We perform a weighted Generalized Linear Model (GLM) using the factors **(F, G)** obtained in Table S2 instead of the original covariates. The estimated regression results under different constraints on number of factors are shown in Table S3.

Propensity Score Weighting Data is grouped into three subsets: the control group with no task switches, the treatment group A with 1 to 3 task switches, and the treatment group B with 4 or more switches. We consider the patient characteristics P as the pretreatment characteristics. With the generalized boosted modeling[4] developed by (1), we estimate a weight $w_{i,t}$ for each data point (patient i, day t). The weight is equivalent to the odds that a randomly selected case with patient characteristics $P_{i,t}$ would fall in the control group (i.e. exploring the treatment effect on the treated group).

Generalized Linear Model: We separately log transform[5] the hospitalist processing time and communication time (right shifted by 1 in case it equals zero before log transformed). The regression equations for patient i on observed day t are then

$\log(\textit{processing time}_{i,t}) = \alpha_{i,t}^{1} + \beta^{1} F_{i,t} + Y^{1} G_{i,t} + U_{i,t}$ (1)

$\log(\text{communication time}_{i,t}+1) = \alpha_{i,t}^{2} + \beta^{2} F_{i,t} + Y^{2} G_{i,t} + V_{i,t}$ (2)

By incorporating the weight $w_{i,t}$ for each data point, we estimate the coefficient with function *svyglm()* in statistical software R. Table S3 compares estimated regression results across constraints on number of factors in **G**: 3 and 4 factors, respectively.

Variable	Estimated coefficient (SD)			
Dependent variable	Equation (1) *log*(Processing time)		Equation (2) *log*(Communication time + 1)	
Factor constraint[1]	3 Factors	4 *Factors*	3 Factors	4 Factors
Intercept	3.14 (0.04)***	3.12 (0.04)***	1.69 (0.08)***	1.68 (0.07)***
Patient characteristics				
F_1	-0.12 (0.10)	-0.16 (0.09)	0.14 (0.23)	0.17 (0.22)
F_2	*-0.14 (0.06)**	*-0.16 (0.06)***	*-0.02 (0.13)*	*-0.03(0.13)*
Team/Hospitalist workflow				
G_1	0.24 (0.10)*	0.29 (0.09)**	-0.01 (0.25)	-0.01 (0.25)
G_2	0.50 (0.06)***	0.49 (0.06)***	0.95(0.10)***	0.93 (0.10)***
G_3	*0.19 (0.05)****	*0.04 (0.04)*	*0.10 (0.11)*	*0.04 (0.07)*
G_4		0.13 (0.05)*		0.05 (0.09)

[1]*The regression covariates are factors obtained from factor analyses: team/hospitalist workflow characteristics are grouped into 3 or 4 factors, patient characteristics are grouped into 2 factors.*

Table S3: Regression results under different factoring constraints. Overall, our results are robust: The significance of each factor stayed the same across models when varying factor constraints—so do the magnitudes of the estimates

Decomposition of processing times

Teamwork interaction effect is equivalent to the differences between observed processing or communication times and predicted ones using original data after nulling the teamwork variables (workflow—task switching, team size and stability—cumulative and daily team sizes, new-member fractions). When nulling some, but not all, variables that make up a factor, we cannot just use the regression coefficient of the factor for counterfactuals but must be more careful. Recall that the grouping results on teamwork variables shown in Table S2 are obtained from **G** such that **[W,T]** = **MG**, subject to COV **(G)** = **I**.

We run 1000 bootstrap iterations: in each iteration we resample 229 data vectors with re- placement and do the following estimation and prediction steps:

1. Run a regression for the sampled data points to obtain estimates for the intercept α, and the coefficients β and γ.

2. Use the original data vector for patient i on observed day t. Set either the task switching variables equal to zero (these will affect factor G2) or the team size and new-member fractions equal to zero (these will affect all three factors in G). Denote these nulled data vector $[\hat{\mathbf{W}},\hat{\mathbf{T}}]_{i,t}$. Holding constant the earlier-estimated factor loadings matrix **M** (estimated under the constraint of 3 factors), we predict a new set of factor values $\hat{G}_{i,t}$ such that $[\hat{\mathbf{W}}, \hat{\mathbf{T}}] = M\hat{G}$, subject to $COV(\hat{G}) = I$.

3. We predict dependent variables by substituting G with the new set of factor values $\hat{G}$ to the equation (1) with the coefficients estimated in step 1 above.[6]

4. For each patient *i* on observed day *t*, we calculate the difference between the observed processing/communication times and the exponentials of the predicted value from step 3. We compute the average difference across patients and days.

At the end we have 1000 values computed in step 4 of each iteration. We report the average and standard deviation of these values.

Future decomposition can be performed by repeating the above 4 steps but only nulling the team size and stability variables (cumulative and daily team sizes, new-member fractions) without changing the workflow variables (task switching) at step 1. The resulting difference at step 4 is equivalent to the team work effect at a macro level, while the remaining of the teamwork interaction effect works via a micro level. A similar decomposition along another dimension physical and digital teams was performed by repeating the above 4 steps, but only letting the physical team variables equal to 0s at step 1. The resulting difference at step 4 is equivalent to the effect accounted by physical teams, while the rest of the teamwork interaction effect comes from the digital teams. The results are summarized in Table S5.

Benchmarking processing times

We construct the three team benchmark evolutions from the merged data set. Each team evolution is constructed using the original data but adjusting some of the team variables discussed in the definition of the benchmark. The construction runs from admission until discharge. We then select the subset that contains the admission day and the days of observation (when the time-motion study is performed) and perform subsequent analyses.

For each benchmark, having constructed the team trajectory, we predict the average processing time with Equation (1). The procedures are similar to the 4 steps above but replacing original team size and stability variables T with the constructed trajectory of physical/digital daily and cumulative team sizes and new-member fractions.

Exploration

Digital *v.s.* Physical team, relationship with time of day when the hospitalist starts documentation

We first look at how these two teams differ when the hospitalist starts documenting a case at various times of day. The 4 plots in

Figure S2 clearly show that the physical team of a patient on a day is more affected by time of day (the two plots on the right) when the hospitalist starts documenting the patient case, compared to the digital team (the two plots on the left).

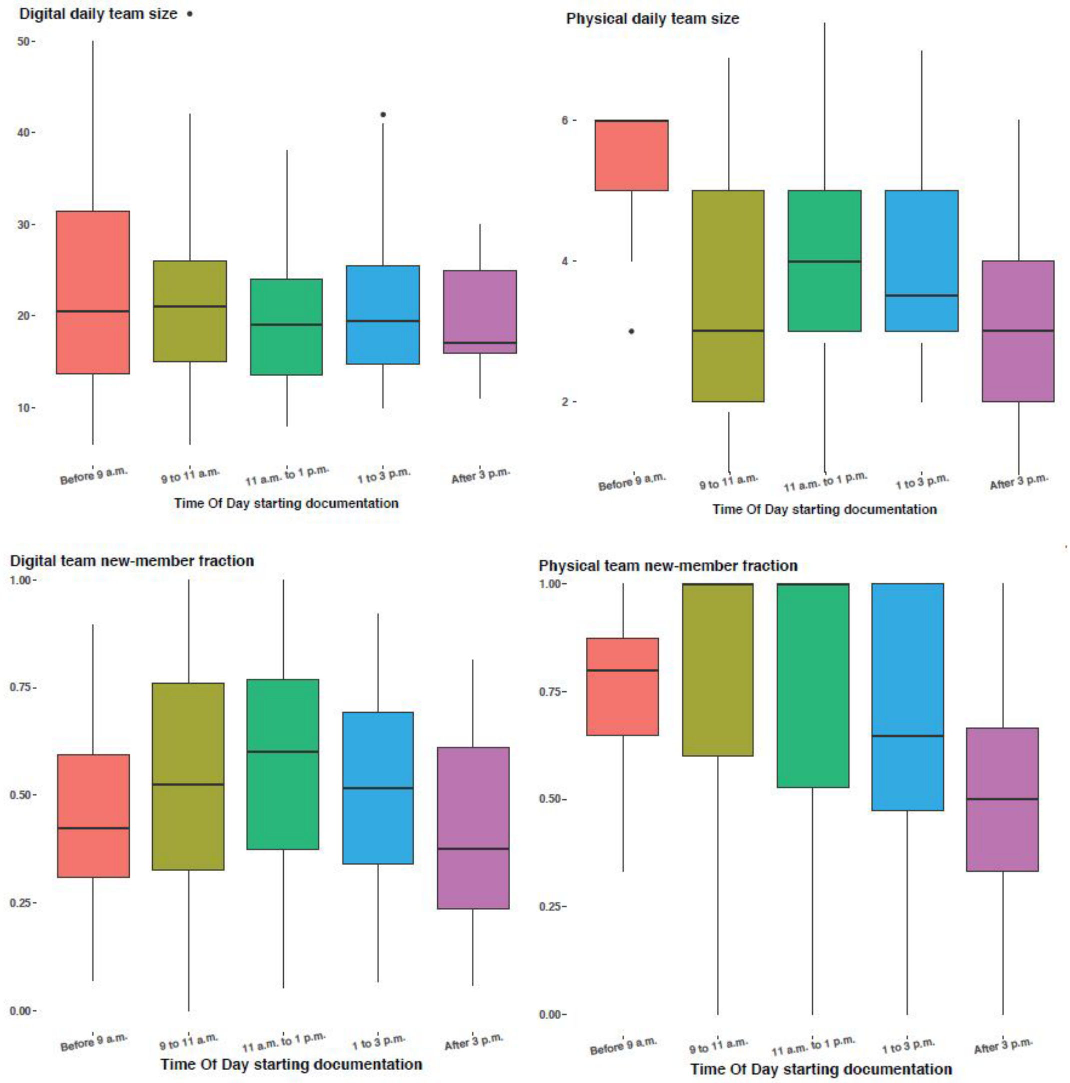

Figure S2: Digital and Physical Daily team size and New-member fraction v.s. Time of day starting documentation

Robustness checks on Factor analysis

In the paper, we performed factor analysis separately on patient characteristics, and on team variables (the last column in Table S4). For the sake of robustness, here, we further perform a factor analysis on the entire variable set (the left of the two columns in Table S4). The decompositions of processing times under both analyses are robust similar in magnitudes, see the first and last columns Table S5. In short, patient characteristics determine 7.2min and 7.5min when factor analysis is performed separately on patient and teamwork variables, and on the entire set, respectively. Similar comparisons can be found in the followings rows that illustrate other decompositions.

Factor analysis performed on:			
All variables		**Separately**	
Patient characteristics,	**Team size, Team stability**	*1) Patient charac-teristics;*	*2) Team size and stability*
Factor analysis result (3 factor constraint)			
Variables	Factor loading	Variables	Factor loading
Factor 1		*Patient Factor 1*	
# days seen by the hospitalist	*0.8*	*Discharge today?*	*-0.4*
Digital new-team fraction	-0.8	Length of Stay	0.9
Physical cumulative team size	0.7	ICU indicator	0.5
Physical new-team fraction	-0.7	*Patient Factor 2*	
Collaboration experience	*0.5*	*# of days seen by the hospitalist*	*1*

Factor analysis performed on:			
All variables		**Separately**	
Patient characteristics,	**Team size, Team stability**	*1) Patient characteristics;*	*2) Team size and stability*
Factor analysis result (3 factor constraint)			
Variables	Factor loading	Variables	Factor loading
Factor 2		*Teamwork Factor 1*	
Discharge today?	-0.3	Digital cumulative team size	1
Length of stay	0.8	*Digital new-team fraction*	*-0.8*
ICU indicator	0.7	Physical cumulative team size	0.7
Digital cumulative team size	0.8	*Teamwork Factor 2*	
Digital daily team size	0.5	# of switches to reach	0.8
Factor 3		# of switches to	0.6
# of switches to reach out	*0.8*	*Physical daily team size*	*0.7*
# of switches to respond	0.6	*Teamwork Factor 3*	
Physical daily team size	0.7	Digital daily team size	0.7
		Physical new-team fraction	0.4
		Collaboration experience	*-0.4*
GLM regression results Variables	Estimated coef (SD)	Variables	Estimated coef (SD)
Intercept	3.14 (0.04)***	*Intercept*	3.14 (0.04)***
Factor 1	-0.04 (0.05)	Patient Factor 1	-0.12 (0.10)
Factor 2	0.21 (0.04)***	Patient Factor 2	-0.14 (0.06)*
Factor 3	0.49 (0.06)***	Teamwork Factor 1	0.24 (0.10)*
		Teamwork Factor 2	0.50 (0.06) ***
		Teamwork Factor 3	0.19 (0.05)***

Table S4: Factor analysis and regression results: grouping all variables together v.s. separately on patient and team variables

	Factor analysis performed:				
	Separately on: 1) Patient 2) Teamwork variables				**on all variables**
	Minimal digital team includes[1]				
	0 person		1 person		
	Average processing time[2]	**Average communication time[2]**	**Average processing time[2]**	**Average communication time[2]**	
Effect					
Actual team	26.1	6.3	26.1	6.3	26.1
Patient-characteristics effect	7.2 (1.0)	0.3 (0.0)	7.4	0.3 (0.0)	7.5 (0.0)
Teamwork interaction effect	18.9	6.0	18.7	6.0	18.6
Further decomposition of teamwork interaction effect on processing times: Macro v.s. Micro levels					
Team size and stability effect	15.4 (1.5)	4.0(0.2)	15.3 (0.2)	4.0 (0.2)	15.5 (0.1)

	Factor analysis performed:				
	Separately on: 1) Patient 2) Teamwork variables				on all variables
	Minimal digital team includes[1]				
	0 person		1 person		
	Average processing time[2]	Average communication time[2]	Average processing time[2]	Average communication time[2]	
Workflow interruption effect	3.5	2.0	3.4	2.0	3.1
Physical v.s. Digital team dimensions					
Physical team explains	10.1 (0.1)	6.0 (0.0)	10.0 (0.0)	6.0 (0.0)	7.1 (0.1)
Digital team explains	8.8	0.0	8.7	0.0	8.4

[1]*When the minimal digital team includes zero person, the patient-characteristics effect is obtained by letting teamwork interaction variables—workflow variables (task switching), physical and digital team variables equal to 0s. Otherwise the digital cumulative and daily team sizes are kept as 1s every day, while the rest teamwork interaction variables are nulled.*
[2]*Both are measured in minutes.*
Table S5: Decomposition of processing times and communications

This alleviates the concern of multicollinearity. Multicollinearity usually is not a big issue if the paper purpose is to predict. Under the presence of multicollinearity, the regression estimate is still unbiased, but the standard deviation of estimated coefficient might be large. Now we show that the predicted (decomposition) results are similar between whether factoring on all or separately on patient and team variables, suggesting that the correlation between patient and team does not cause large standard deviation of estimates. Factor analysis is traditionally performed for the sake of easier interpretation of variables (and, but not necessarily, reduce multicollinearity). We will go with the factor analysis that is performed separately on patient and team variables since otherwise it is hard to interpret the team effect (which is grouped with patient variables).

	Dependent variable:					
	New-member fration		**Daily team size**		**Cumulative team size**	
	Digital	**Physical**	**Digital**	**Physical**	**Digital**	**Physical**
Intercept	0.93***	1.04***	29.02***	1.83**	19.25	-1.14
	(0.12)	(0.17)	(3.44)	(0.84)	(18.29)	(1.26)
Discharge?	-0.15***	-0.06	-8.11***	0.07	14.54***	-0.03
	(0.04)	(0.08)	(1.01)	(0.32)	(4.37)	(0.81)
PCP-NMH?	-0.02	-0.08*	-1.19	-0.20	-0.71	0.28
	(0.03)	(0.05)	(1.21)	(0.26)	(7.01)	(0.45)
Number of days seen by the hospitalist	-0.13***	-0.21***	-1.53***	-0.09	12.63***	1.75***
	(0.02)	(0.04)	(0.52)	(0.16)	(3.18)	(0.39)
Length of Stay	-0.00***	-0.00	0.01**	0.00	0.22***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Acuity level	-0.01	0.01	0.58	0.22	0.36	0.19
	(0.02)	(0.03)	(0.53)	(0.16)	(3.02)	(0.22)
ICU indicator	-0.06	-0.031	2.63	0.16	42.36***	-0.88
	(0.05)	(0.07)	(1.96)	(0.29)	(10.72)	(0.54)
Time of Day	0.00	-0.00	-0.54**	0.05	-2.81**	-0.07
	(0.01)	(0.01)	(0.24)	(0.06)	(1.18)	(0.09)
Number of other patients in pipe-line	0.00	0.03**	-0.04	-0.03	0.86	-0.18**
	(0.01)	(0.01)	(0.32)	(0.06)	(1.21)	(0.09)
Observations	231	231	231	231	231	231

*p<0.1; **p<0.05; ***p<0.01
Table S6*:* GLM regression results: regressing team variables on patient variables

	Dependent variable: # of switches		
	to respond	**to reach out**	**in total**
Intercept	0.11	0.43	0.54
	(0.27)	(0.29)	(0.46)
Discharge?	0.05	-0.12	-0.07
	(0.19)	(0.21)	(0.33)
PCP-NMH?	-0.13	0.04	-0.10
	(0.15)	(0.16)	(0.25)
Number of days seen by the	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Length of Stay	-0.10	0.00	-0.10
	(0.11)	(0.11)	(0.18)
Acuity level	-0.40	-0.43	-0.83
	(0.36)	(0.38)	(0.61)
ICU indicator	-0.09**	-0.11**	-0.20***
	(0.04)	(0.05)	(0.07)
Time of Day	0.00	0.01	0.01
	(0.04)	(0.04)	(0.07)
Number of other patients in pipeline	-0.15	0.47	0.32
	(0.70)	(0.75)	(1.20)
Digital new-team fraction	0.09	0.08	0.17
	(0.45)	(0.48)	(0.77)
Physical new-team fraction	0.02	0.02	0.04
	(0.02)	(0.02)	(0.03)
Digital daily team size	0.27***	0.42***	0.69***
	(0.05)	(0.05)	(0.09)
Physical daily team size	0.01**	0.01	0.01**
	(0.00)	(0.00)	(0.01)
Digital cumulative team size	-0.03	-0.01	-0.05
	(0.04)	(0.04)	(0.06)
Physical cumulative team size	1.30	0.43	1.73
	(0.90)	(0.97)	(1.54)
Observations	231	231	231

***p<0.1; **p<0.05; ***p<0.01**

Table S7: GLM regression results: regressing workflow interruptions on team variables

	Digital new-member fraction	Physical new-member fraction	Digital daily team size	Physical daily team size	Digital cumulative team size	Physical cumulative team size	# of switches to respond	# of switches to reach out	Collaboration experience	Discharge today?	PCP employed by NMH?	# of days seen by the hospitalist	**Length of Stay**	Acuity level	ICU indicator	Time of Day
New-member fraction																
Digital	0.6***															
Physical																
Daily team size																

Digital	0.2***	0.2**														
Physical	0.2**	0.3***	0.2**													
Cumulative team size																
Digital	-0.7***	-0.3***	0.3***	0.0												
Physical	-0.6***	-0.6***	0.0	0.0	0.6***											
# of switches																
to respond	0.0	0.2**	0.2**	0.4***	0.1	0.0										
to reach out	0.2*	0.2***	0.2*	0.5***	0.0	0.0	0.5***									
Collaboration experience	0.2***	-0.5***	-0.1	-0.2*	0.1	0.3***	-0.1*	-0.1								
Discharge today?	-0.1	0.0	-0.6***	0.0	-0.2**	-0.1	0.0	0.1	0.1							
PCP employed by NMH?	0.0	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0						
# of days seen by the hospi-talist	-0.6***	-0.6***	-0.1	-0.1	0.5***	0.6***	-0.1	-0.1	0.4***	0.1	0.0					
Length of Stay	-0.5***	-0.2**	0.4***	0.0	0.8***	0.5***	0.1	0.0	0.0	-0.3***	-0.1	0.3***				
Acuity level	0.0	0.1	0.0	0.1*	-0.1	-0.1	-0.1	0.0	-0.1	0.0	0.0	-0.2*	-0.1			
ICU indicator	-0.3***	-0.1	0.3***	-0.1	0.7***	0.2**	0.0	-0.1	0.0	-0.2***	0.0	0.2*	0.52***	0.04		
Time of Day	-0.1	-0.2*	-0.1	-0.1	0.1	0.1	-0.2**	-0.2***	0.0	-0.1	-0.1	0.1	0.1	0.1	0.1	
# of other patient EHRs in pipeline	0.1	0.1	0.1	0.0	-0.1	-0.1*	0.0	0.0	-0.2***	0.0	0.0	0.0	-0.1	-0.1	0.1	0.2**

This correlation table shows that both # of switches to respond and to reach out positively correlate with: physical new-member fraction, physical daily team size, and digital daily team size, while # of switches to reach out also correlates with digital new-member fraction. The magnitudes of these correlations are larger for physical team variables, compared to those for digital team variables.

Table 8: Correlation among team, hospitalist workflow and patient variables

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