Fit as a Fiddle or Sick as a Dog: Effects of Patient Discharge Preferences on Uptake of Clinical Decision Support

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Running Head: Uptake of Decision Support and Patient Preferences

Abstract

The Centers for Medicare and Medicaid Services has identified unplanned hospital readmissions as a critical healthcare quality and cost problem. Improvements in hospital discharge decision-making and post-discharge care are needed to address the problem. This paper reports behavioral research on improving hospital discharge decisions. The paper reports a field experiment with clinical decision support (CDS) for hospital discharge decision-making. Use of CDS significantly decreased unplanned readmissions and hospital length of stay in previously-reported laboratory experiments with virtual patients. Previous research did not address opposing problems that can occur: (1) there can be negligible uptake of CDS by providers; or (2) providers can become over-reliant on CDS and underuse other information. The field experiment researches discharge decision-making when subjects are provided CDS information or subjective reports by standardized patients or both. Subjective information about readiness for discharge was obtained during examinations of standardized patients, who are regularly employed in medical education, but in our experiment had been given scripts developed for the experimental treatments. The CDS tool presents evidence-based discharge recommendations obtained from econometric analysis of data from de-identified electronic health records of hospital patients. Decision-makers in the experiment were third and fourth year medical students. 38 participants discharged eight simulated patient encounters with an average length of stay 8.06 in the CDS group versus 8.84 days in the Control group. Odds of discharging a patient, on days not classified as "Ready for Discharge," decrease by 58% (CDS assisted) and 51% (Control) for standardized patients reluctant to be discharged. For standardized patients eager to be discharged, odds of discharge are not affected for CDS supported decisions but in Control treatment they almost doubled in days the patient is classified as "Not Ready for Discharge." These findings indicate that (1) participants are not over-relying on CDS and (2) CDS may help avoid prematurely discharging patients with preference for being discharged.

Introduction

Historically, the Centers for Medicare and Medicaid Services (CMS) has incurred over $17.5 billion in additional hospital charges annually from the 10-20% of its covered patients with unplanned hospital readmission within 30 days after discharge [1]. For the total U.S. inpatient population, the costs of hospital readmissions is over $41 billion annually [2]. The rate of unplanned readmissions is a metric for low quality healthcare as well as a cost inflator [3]. As a result, CMS has penalized hospitals with higher-than-expected readmission rates [4].

One of the most direct opportunities to reduce hospital readmission rates is to increase patients' hospital length of stay (LOS) [5,6] , given that more than 30% of readmissions occur within a week after discharge [7]. However, increasing the average LOS overburdens health systems worsening access to care and increasing total healthcare costs [8]. Therefore, a more targeted option for reducing hospital readmission rates is to prioritize discharging of patients that are most likely to avoid readmission, and vice versa [8,9]. Clinical decision-support (CDS) tools may offer a low-resource and high-quality selection mechanism [10–12]. Such an approach may be particularly beneficial to surgical patients who exhibit well-established risks for readmission. Specifically, reported inconsistencies among surgeons' stated discharge criteria, algorithmic estimates of their actual discharge criteria [13], and empirical criteria that predict unplanned readmissions suggest that discharge decision-making can be improved by application of evidence-based discharge criteria at the point of care [9,14].

Application of complex but existing knowledge may be most easily facilitated by a data-driven CDS tool. Historically, CDS tools have been difficult to implement and inefficient for real-time use [15–18]. We have previously reported laboratory experiments in which subjects' uptake of CDS patient discharge selection criteria improved discharge decision-making [9,13,19]. But these prior studies did not incorporate how patient-clinician interactions may affect this decision-making process.

An open question is whether providers can integrate CDS objective information with subjective information obtained from examining patients to arrive at better discharge decisions which decrease length of stay *and* readmission rate. This question is central because of two opposing problems that can occur with *any* CDS tool: (1) there can be negligible uptake of the CDS tool by providers; or (2) the providers can be over-reliant on the CDS tool and underuse other information including subjective reports by patients. The purpose of this study was to use a behavioral experiment with clinician decision-makers and standardized patients to investigate the impact of human interaction on the discharge decision and the uptake of recommendations provided by the CDS tool. Results from the experiment will provide additional information relevant to decisions about introducing the CDS tool on patient wards.

Methods

Medical students were recruited for a 2×2 incentivized behavioral experiment with standardized patients to assess discharge practices following simulated surgical encounters with and without a decision-support tool and when interacting with different patient discharge preferences ("Eager" versus "Reluctant"). The multivariable treatment effects of decision-support and patient discharge preferences were assessed for length of stay and likelihood of readmissions. Finally, we tested for the differential effects and concordance of decision-support recommendations on discharge decisions with different patient preferences. Results were compared to the authors' prior experiments [9] without standardized patients.

Study Design

We conducted a 2x2 behavioral field experiment comparing bedside clinician decision-makers with and without a CDS tool in relation to patients who are Eager versus Reluctant for discharge as shown in Figure 1.

Figure 1. 2×2 behavioral experimental design

Patient Discharge Preference	Availability of Clinical Decision Support (CDS)[a]: CDS Available	Availability of Clinical Decision Support (CDS)[a]: Control
Reluctant	CDS, Reluctant Patient	Reluctant Patient
Eager	CDS, Eager Patient	Eager Patient

a. Four relevant groups of participants randomly assigned to whether they had the availability of a decision support tool and for each encounter with a patient eager or reluctant for discharge.

Because these interactions are difficult to measure with real patient encounters, this form of behavioral study favored a simulated decision-making environment. Therefore, we recruited medical students to engage with a simulated hospital patient ward with standardized patients and using a medical school's mock examination rooms traditionally used for the teaching curriculum's Objective Structured Clinical Examinations (OSCE). We designed the experimental sessions to last approximately 2.5 hours. These results were compared to our group's prior discharge decision experiment without the use of standardized patients [9]. This study was approved by the Emory University Institutional Review Board and the Georgia State University Institutional Review Board.

Participant Clinician Population

We recruited third and fourth year medical students to model clinician decision-making. The standardized patients included in this study were professional actors with prior training as standardized patients and disease-specific education for their roles in the experiment. All participants had prior experience in their role as decision-maker or patient within the medical school's OSCE program. Instructions provided to the subjects are contained in S1 Appendix.

Virtual Patient Population

We initially created 30 virtual patients using data from the electronic medical records of 30 real hospitalized patients, previously described for the prior virtual decision-making experiment without standardized patients [9]. For the standardized patient version, we randomly selected eight patients from the pool of these thirty virtual patients whose procedures were from the upper two-thirds of readmission risk (i.e., greater than 10% readmission risk) for all hospital stays. All participants in the previously reported virtual experiment as well as in the standardized-patient experiment reported herein were provided with identical daily clinical data on these eight patients.

Standardized Patient Population

A cadre of around 100 actors, trained to portray a variety of illnesses and conditions, work at OSCE. These skilled professionals present clinical scenarios in a standardized fashion, thus earning the title of "standardized patients." Each standardized patient was matched with the de-identified EHR of a distinct real patient included in the virtual patient population. Each standardized patient was given enough information about the specific illness and course of treatment of the real patient they would portray to serve as a proxy for the real patient in an OSCE examination room (see example in S2 Appendix).

Experimental Comparison

In one session, a specific standardized patient portraying a specific real patient would be instructed to present herself as eager to go home ("fit as a fiddle"). In another session with different clinician decision-makers, the same standardized patient portraying the same real patient would be instructed to present herself as reluctant to go home ("sick as a dog"). Subjective standardized patient instructions varied between two sessions but objective clinical data was identical. See S3 Appendix for an example of Eager and Reluctant standardized patient instructions. The clinician decision-makers all had complete access to the clinical variables for each case and participated in an exam encounter with the standardized patient. All decision-makers encountered four Eager and four Reluctant standardized patients.

The decision-makers were randomized to treatments with a clinical decision-support tool with discharge recommendations ("CDS Supported") or treatments without CDS ("Control"). The prediction model and the visualization of the CDS tool have been previously described [9,19]. The model includes a dynamically updated daily probability of readmission within 30 days of discharge for a specific patient using clinical, demographic, and census data. The CDS recommended "discharge patient" if the 80% upper bound of the confidence interval of the probit estimate of readmission risk was 10% lower than the historical readmission rate for a given procedure. In this way, a current discharge decision can be informed by the aggregated experience with thousands of similar patients with known histories from the same institution. Such CDS provides a statistically informed answer to the central question: "If this patient is discharged today, what is the likelihood of unplanned readmission within 30 days?"

The clinician decision-makers were rotated through eight standardized patient encounters in each experimental hospital day. The median number of experimental days for all eight patients to be discharged was 7 (lower and upper quartiles were 6 and 8). The median number of discharge decisions was 31 (lower and upper quartiles were 25 and 36). The operations for each patient encounter focused on

intensive abdominal surgical procedures including: complex hepatobiliary reconstruction, pancreas resection, palliative gastrojejunostomy, pelvic exenteration, and colectomy. Participants' order in the rotation of encounters was randomly determined. Each clinician decision-maker would first review clinical information and CDS output updated to the current experimental hospital day using a laptop computer outside the OSCE examination room. The participant would then enter the examination room to interview the patient, perform an exam, and after that enter his or her decision into the laptop of whether to discharge the patient on that experimental day. Whether each standardized patient was ultimately readmitted was determined by a random draw from a binomial distribution of the probit point estimate of readmission probability for the discharge day. To incentivize discharge-motivated clinician behaviors, each discharged patient that did not get readmitted generated a $15 payment to the clinician decision-maker ($120 maximum possible payout). Participants' disincentive for prematurely discharging patients was that they would not be able to carry an additional patient on their "service" if an experimental day were occupied by a readmitted patient; thus, losing an additional opportunity for a discharge and its associated payout [9] .

Other Sources

Data from the 2×2 field experiment reported herein is also compared to data from the laboratory experiment previously reported [9] for the same virtual patients. Since the EHR data for the eight patients used in the OSCE field experiment were also used in the laboratory experiment, comparison of discharge decision responses for these eight patients between the two experiments provides additional insight into the effects of subjective information on quality of discharges and the uptake of evidence-based discharge criteria in the CDS tool.

Variables

For each decision-maker participant, we collected demographic information including gender, medical school GPA, undergraduate GPA, musical background, athletic background, and risk attitudes.

For each patient encountered, we recorded whether the patient was discharged, the patient's length of stay, and whether the patient was readmitted.

Statistical Analysis

Participants' demographics in the CDS Supported and Control groups were statistically compared using t-test for continuous variables and Fisher's exact test for categorical variables. We used ordinary least squares regression with robust standard errors clustered at the participant level to estimate two individual treatment effects (1: decision support available; 2: patient discharge preference) and other determinants of length of hospital stay. For the quality of discharge decisions, we used logistic regressions (with robust standard errors clustered at the participant level) to estimate the two individual treatment effects and other determinants of the likelihood of a patient being readmitted. To estimate the differential effects of patient discharge preference (Reluctant versus Eager) and type of recommendation (discharge versus do not discharge) on CDS uptake we used t-tests to compare participants' compliance rates with CDS recommendations.

Results

We recruited 38 clinical decision-maker participants. For the purpose of comparison, the statistical analysis reported below includes 47 subjects from the previously reported virtual patient experiment where indicated [9]. Participants were statistically more likely to be female ($p=0.049$, Fisher's exact test) in the standardized experiment's control group, and all other demographic variables were no different for each experiment and overall (S4 Appendix).

The average length of stay in the standardized patient experiment was 8.06 days in the CDS Supported group versus 8.84 days in the Control group; the average length of stay in the virtual experiment was 6.6 days in the CDS Supported group and 7.6 days in the Control. When the average length of stay was compared between decision-making groups, the CDS Supported group reduced length

Table 1. Linear regression (OLS) model of length of stay on decision-support availability, degree of readmission risk, and patient preference for discharge with and without adjusted covariates.

	Standardized Patients		**Virtual Experiment**	
	Unadjusted (Robust SE) p-value	Adjusted (Robust SE) p-value	Unadjusted (Robust SE) p-value	Adjusted (Robust SE) p-value
Constant (Baseline length of stay)	3.692 (0.437) <0.001	3.349 (2.882) 0.253	5.672 (0.304) <0.001	6.963 (2.964) 0.023
Start Date	0.651 (0.058) <0.001	0.651 (0.058) <0.001	0.336 (0.044) <0.001	0.336 (0.044) <0.001
High Readmission Risk	0.820 (0.327) 0.017	0.809 (0.336) 0.021	1.226 (0.351) 0.001	1.217 (0.361) 0.002
CDS Supported	-0.965 (0.377) 0.015	-1.197 (0.421) 0.007	-1.296 (0.381) 0.001	-1.226 (0.366) 0.002
CDS Supported + High Readmission Risk	0.303 (0.326) 0.358	0.315 (0.337) 0.357	0.220 (0.390) 0.575	0.252 (0.405) 0.537
Discharge Reluctant	2.097 (0.284) <0.001	2.104 (0.288) <0.001		
n	306	306	402	402
N clusters	38	38	47	47
R^2	0.588	0.596	0.265	0.282

Notes. The dependent variable is the length of hospital stay. Parentheses contain robust standard errors clustered at the subject level. Two-sided p-values reported below (robust) standard errors. Adjusted covariates not shown include: Undergrad GPA, Medical School GPA, Female, Musical training, Athletic training, Risk Attitudes.

of stay by approximately one day. This finding was upheld in both the virtual and the standardized patient experiments with an adjusted reduction in length of stay in the standardized patient experiment of 0.8 days ($p = 0.015$, two-sample t-test) and 1.2 days ($p = 0.001$, two sample t-test) in the virtual experiments. Table 1 also demonstrates that the Eager behavior type versus the Reluctant behavior type reduced the length of stay by two days ($p < 0.001$). We get similar qualitative results for censored regressions. For Standardized Patients, there are 42 left-censored observations and 264 uncensored observations. For model specification with covariates, the estimated coefficient for "Discharge Reluctant" patient is 2.44 (p-value<0.001) and for "CDS Supported" is -1.27 (p=0.006). In Virtual experiment, there are 43 (left-censored), 338 (uncensored) and 21 (right-censored) observations. The estimated coefficient for "CDS Supported" is -0.92 (p=0.014).

Table 2 demonstrates the results of the use of a CDS tool on the risk of unplanned readmission. Longer lengths of stay were protective against readmission ($p < 0.001$). Patients deemed high risk for readmission indeed had more than 3 times the odds of readmission in the standardized patient experiment ($p = 0.021$) and more than 5 times the odds of readmission ($p = 0.013$) in the virtual experiment. With standardized patients, there was a borderline significant ($p = 0.100$) effect in the CDS Supported group with an 80% decrease in odds of being readmitted for high risk patients.

Table 2. Multivariable logistic regression of readmission risk on decision-support availability, degree of readmission risk, and patient preference for discharge with/without adjusted covariates.

	Standardized Patients		**Virtual Experiment**	
	Unadjusted OR (Robust SE) p-value	Adjusted OR (Robust SE) p-value	Unadjusted OR (Robust SE) p-value	Adjusted OR (Robust SE) p-value
Length of Stay†	0.062	0.065	0.158	0.134
	(0.046)	(0.048)	(0.075)	(0.070)
	<0.001	<0.001	<0.001	<0.001
High Readmission Risk	3.265	3.246	5.584	5.971
	(1.582)	(1.661)	(3.894)	(4.308)
	0.015	0.021	0.014	0.013
CDS Supported	1.099	1.040	1.703	2.018
	(0.615)	(0.561)	(1.032)	(1.252)
	0.866	0.942	0.379	0.258
CDS Supported +	0.218	0.212	0.338	0.333
High Readmission Risk	(0.198)	(0.200)	(0.253)	(0.247)
	0.094	0.100	0.147	0.138
Discharge Reluctant	1.030	1.058		
	(0.524)	(0.603)		
	0.954	0.921		
n	306	306	381	381
N clusters	38	38	47	47
Pseudo R^2	0.130	0.169	0.072	0.108

Notes. Dependent variable is a binary variable that takes value 1 if a patient is readmitted after being discharged. Parentheses contain robust standard errors clustered at the subject level. Adjusted covariates not shown include: Undergrad GPA, Medical School GPA, Female, Musical training, Athletic training, Risk Attitudes.
† Natural logarithmic transformation for better fit.

In the virtual experiments, concordance between decision-support recommendation and actual participant decision was 78% in the CDS Supported group versus 63% in the Control, revealing an effect of exposure to a CDS tool of increasing concordance by 15% (p=0.014). With the standardized patient encounters, concordance in the CDS Supported group decreased to 63% while the Control group was

59%, suggesting only a 4% treatment effect (p=0.462). The net treatment effect of CDS was observed to be much more substantial in the Reluctant group (0.081 increase in concordance) versus in the Eager group (0.01 increase in concordance). In both experiments, participants were less concordant when the CDS recommendation was "Discharge," likely reflecting the inherent risk aversion of discharge decision-makers. Table 3 reports the summary results of concordance.

Table 3. Concordance between decision-support recommendation and study participant's actual decision to discharge stratified by standardized patient preference for discharge.

Standardized Patients		**Standardized Patients**			**Virtual Experiment**
Treatment	Recommendation	Reluctant	Eager	Reluct.+Eager	
CDS Supported	"Discharge"	0.38	0.58	0.38	0.60
	"Do not Discharge"	1.00	0.89	0.95	0.94
	All Recommendations	0.59	0.68	0.63	0.78
Baseline	"Discharge"	0.25	0.51	0.48	0.33
	"Do not Discharge"	1.00	1.00	1.00	0.92
	All Recommendations	0.51	0.67	0.59	0.63
Net CDS Effect	"Discharge"	0.124 (0.018)	0.069 (0.410)	-0.096 (0.082)	0.273 (<0.001)
	"Do not Discharge"	0.00 …	-0.111 (0.347)	-0.053 (0.324)	0.021 (0.456)
	Both	0.081 (0.387)	0.01 (0.898)	0.05 (0.462)	0.15 (0.014)

Notes. Table reports averages of subjects' mean consistency rates across treatments. Consistency variable takes value 1 if subject's discharge decision is the same as the CDS recommendation; discharge decisions on days for which CDS tool makes no recommendation are not included. For each subject, we created the mean consistency rate for each recommendation (Discharge, Do not Discharge) and for each patient type (Reluctant, Eager). Data from the standardized patient experiment are used in the first three columns whereas the third column uses data from the laboratory experiment. Two-sided *p*-values (in parentheses) in Net CDS Effect part of the table are for the t-test.

Table 4 shows that patient discharge preferences can affect clinician decision-making with and without a decision-support tool. Odds of discharging a Reluctant standardized patient decrease by 57.5%

(=1-0.425, p<0.001) when CDS assisted and by 51% (1-0.493, p<0.001) in the Control treatment but there is no "Reluctant" patient effect on days the patient is "Ready for Discharge." These estimates suggest that participants are not over-relying on CDS and they are more cautious about discharging a patient whose behavior signals they do not feel ready to be discharged on days the patient is not classified as "Ready for Discharge." There is no effect of Eager standardized patient on odds of

Table 4. Patient behavior effects on discharge decisions.

Adjusted Odds Ratio (Robust SE) p-value	**Reluctant Discharge Preference (or none)**			**Eager Discharge Preference (or none)**	
	CDS Supported	**Control**		**CDS Supported**	**Control**
Reluctant	0.425 (0.113) 0.001	0.493 (0.107) 0.001	Eager	1.533 (0.441) 0.138	1.511 (0.400) 0.119
Reluctant x Clinically Ready for Discharge[a]	0.530 (0.273) 0.218	1.157 (0.430) 0.695	Eager x Clinically Not Ready for Discharge[b]	0.604 (0.238) 0.201	2.304 (1.046) 0.066
Clinically Ready for Discharge[a]	2.842 (1.093) 0.007	1.963 (0.733) 0.071	Clinically Not Ready for Discharge[a]	0.119 (0.038) 0.000	0.034 (0.016) 0.000
N	1,071	1,475		933	1,291
Nr of Clusters	42	43		42	43
Pseudo R^2	0.113	0.143		0.195	0.221

Notes. Dependent variable: An indicator variable that takes value 1 if the patient is discharged. Treatment variables: Dummy variable for a standardized patient (Reluctant or Eager), dummy variable for Clinical Readiness for Discharge (Not Ready or Ready). All columns report Odds Ratios derived from Logit estimates. Robust standard errors (clustered at the subject level) in parentheses. Two-sided p-values reported below (robust) standard errors. Data from the laboratory experiment and from the standardized Reluctant patient group were combined for the left two columns versus laboratory experiment results and the Eager patient group for the right two columns. Covariates not shown include: day of hospital stay, Undergrad GPA, Medical School GPA, Female, Musical training, Athletic training, Risk Attitudes.

[a] "Ready for Discharge" was categorized based on the fourth quartile of day of discharge in the virtual experiments without CDS.

[b] "Not Ready for Discharge" was categorized based on the first quartile of day of discharge in the virtual experiments without CDS.

discharge for CDS-assisted decisions. As shown in the second row and right-most column, in the control treatment the odds of discharge of an Eager standardized patient more than double (to 2.304, p=0.066) in days they are classified as "Not Ready for Discharge." This suggests that, absent CDS, patients with preferences for discharge may be prematurely discharged.

Conclusion

A central purpose of this study was to use behavioral experiments with clinician decision-makers and standardized patients to study whether providers can integrate CDS objective information with subjective information obtained from examining patients to arrive at better discharge decisions. Would decision-makers' discharge choices reflect use of both CDS information and patient reports or would they neglect one source of information and over-rely on the other?

One-half of the subjects (i.e., clinician decision-makers) in the experiment participated in sessions using the Baseline (Control) information from a facsimile of de-identified EHRs. The other one-half of the subjects participated in sessions with the CDS treatment and the EHR facsimile. All subjects also received information from examining standardized patients. Subjects in the experiment had previous experience with examining standardized patients in the OSCE patient rooms as part of their medical education.

Each of the standardized patients was given instructions for portraying an individual hospital patient with a specific illness and course of treatment. In addition, one-half of the standardized patients in each session were given instructions to report feeling well and being eager to go home; these are referred to as Eager patients. The other one-half were given instructions to report feeling badly and being reluctant to be discharged; these are referred to as Reluctant patients. In a second, paired session with different (clinician decision-making) subjects the role of a specific standardized patient was reversed between Eager and Reluctant. Each subject encountered both Eager and Reluctant standardized patients in each session.

Results from the standardized patient experiments support uptake of the CDS discharge recommendations. Length of stay was improved by one day in participants using the decision support tool versus those without it. However, that uptake was significantly decreased by the introduction of subjective patient behavior reluctant to be discharged. In Reluctant patients, LOS increased by over two days (compared to Eager patients) and provider consistency with the decision support tool's recommendation decreased by about 20%. The patient-reported reluctance for discharge had a significant impact on discharge decision making regardless of whether the information provided by the patient was consistent with the readmission-risk implications of EHR data used by the CDS tool.

In this group's prior laboratory experiment, there was asymmetric uptake of the CDS recommendations, with participants being less willing to adopt "Discharge Patient" recommendations than "Do Not Discharge" recommendations. Findings from this study suggest further interaction effects between uptake of CDS recommendations and patients' own preferences about discharge. Table 3 highlights the amplifier effect where the likelihood of patient discharge decreased significantly when the CDS recommendation was "Discharge" but the standardized patient was randomized to "Reluctant". Similarly, the likelihood that the patient was discharged was higher when a "Discharge Patient" CDS recommendation coincided with an "Eager" patient type than when it diverged from a Reluctant patient type. Participants are more likely to adhere to CDS recommendations when concordant with patient preferences but participants' decisions reflected both patient discharge preferences and CDS discharge recommendations.

Limitations

Limitations of this study include the intrinsic *ex vivo* nature of behavioral laboratory experiments and the small participant population. Behavioral laboratory experiments are useful when large-scale experiments in a real clinical environment are not practical. In the case of discharge decision-making, the heterogeneous nature of hospital discharges would mean the ongoing collection of hundreds of patients'

clinical data as well as their psychosocial preferences in order to observe how patient behavior affected discharge decision-making recommendations with and without CDS tools. In the particular institutional setting of this study, the role of this investigation was to help better understand these human-machine interactions prior to deployment. We have tried to mitigate any effects of a laboratory-based setting by appropriately incentivizing participants and using real clinical data that is comparable to what would be encountered by these decision-makers in their clinical roles. It is also encouraging that we have seen similar decision-making phenomena over the various iterations of these experiments using different participants and different selected patients.

Next Steps

A remaining open question is whether providers can integrate CDS objective information with subjective information obtained from examining patients on patient wards to arrive at better discharge decisions which decrease length of stay *and* readmission rate. This question is central because of two opposing problems that can occur with *any* CDS: (1) there can be negligible uptake of the CDS by providers; or (2) the providers can be over-reliant on the CDS and underuse other information. The next step in testing the CDS will come from a field experiment in the form of an intervention on patient wards. Before that is possible, we are developing a beta version of the CDS that can interact with EHR in real time.

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Welcome

Team Members:

Dr. John F. Sweeney

Dr. James C. Cox

Dr. Kurt E. Schnier

Dr. Vjollca Sadiraj

Kevin Ackaramongkolrotn

Connie Coralli

Gina Shannon

Val Brown

William Knechtle

Main Idea

You are participating in a study about post surgical discharge decisions

Today you'll be rounding on 8 post surgical patients.

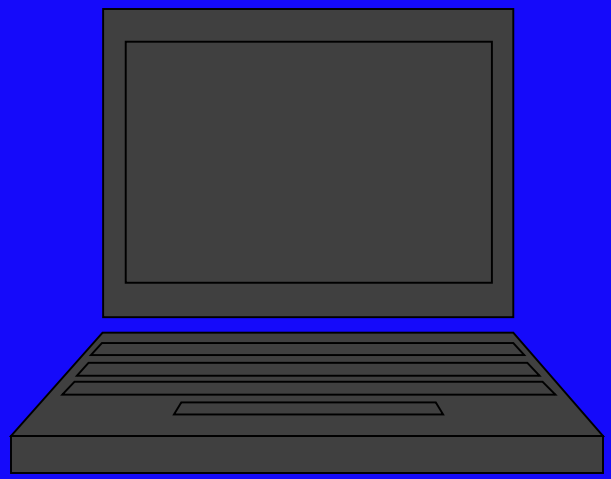
You'll be rounding on them "daily" until you have discharged everyone.

Schedule

- You will be given a list of room numbers which will show the order in which you are to rotate. You will be provided a laptop which you will carry with you during your rounds.

- There is an ID number on the top of your "rounding" schedule – If you want to get paid you'll need to turn in this ID number at the end of the experiment.

Experiment.	*Your ID: #Z##Z#Z*
Schedule	
Room 1	
Room 6	
Room 5	
Room 7	
Room 2	
Room 4	
Room 3	
Room 8	



Schedule

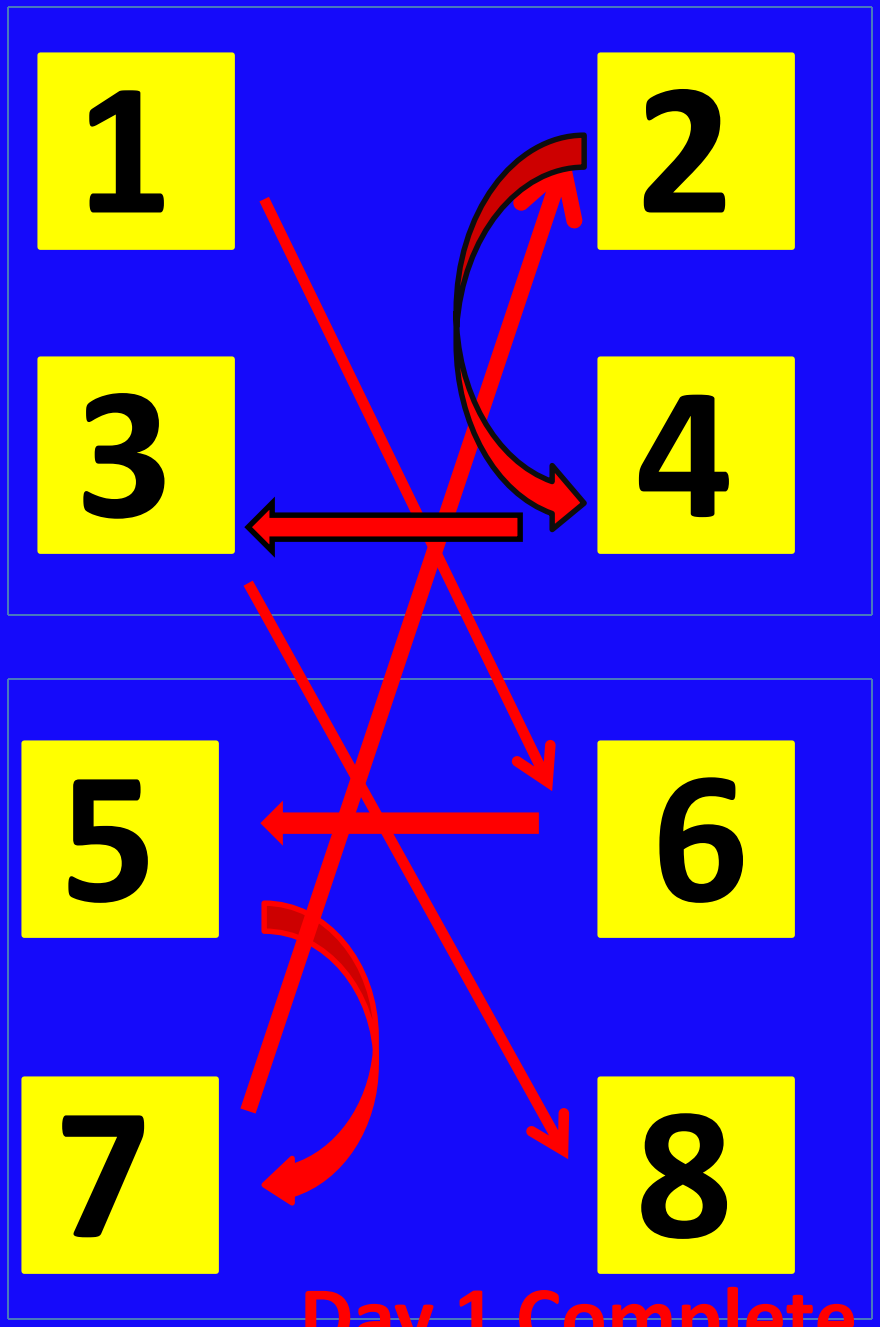
Your first patient will be the one in the top row of your list.

1. **Go to the room in the top row of your list**
2. **Look at the patient's name on the door**
3. **Find that patient's information in your computer.**

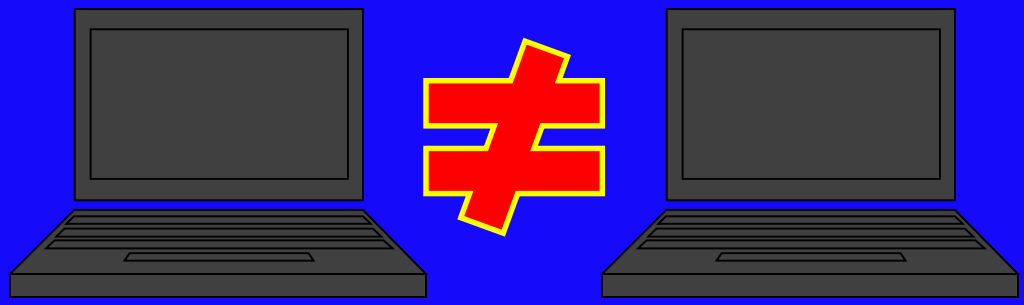
Do not open the patient's information until you are outside that patient's door.

SCHEDULE EXAMPLE

Experiment.	Your ID: #Z##Z#Z
Schedule	
Room 1	
Room 6	
Room 5	
Room 7	
Room 2	
Room 4	
Room 3	
Room 8	



- On the laptop you will find various records for each of your patients.
- Some of them may contain “decision support” information which you may use or not as you see fit.
- The information you are provided from the records and patient may vary from one patient to another.
- The information each of you gets may vary one to another.
- Avoid allowing the behavior or other students to influence your behavior.

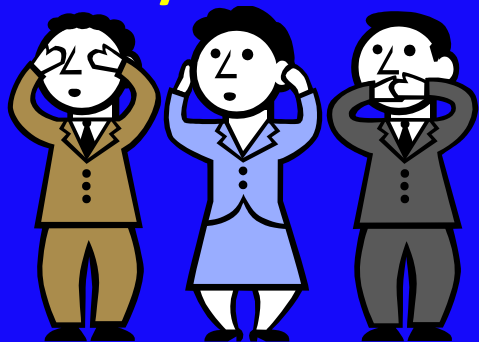


Rules

- No discussions about the cases or the structure of the experiment are allowed.

- No use of technology other than the computerized records is allowed. Your cell phones must be off. Please turn them off at the beginning of the experiment and do not turn them back on until the experiment is finished.

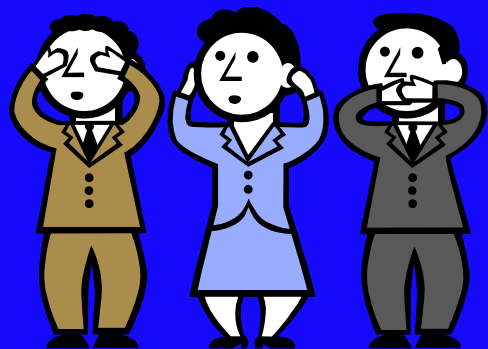
- You will be seeing standardized patients today and, as always, your interactions with them should be limited to those you would have with any other patient.



Rules (continued)

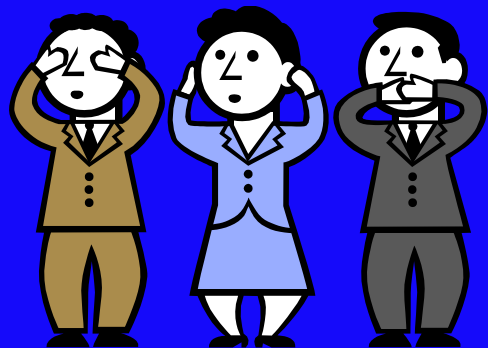
- Do not inquire about what's happened with other students.

- Each of you has a list of patients that is unique and distinct. Please make no inferences about what or how other subjects are doing.



When you discharge a patient

- The patient name will disappear from the patient list on your computer whether or not the discharge was successful.
- If you receive a message that a discharged patient was readmitted, please don't share this with the patients or other subjects.
- Nor should you make any inferences about the subsequent readmission as you will not be managing that admission.



Money

- On each experimental day you'll be expected to make a decision to discharge or not to discharge. For each "successful" decision, i.e. for each discharged patient who's not readmitted, you'll be paid $15.

- You will not be paid for discharged patients who are readmitted.

- There is an ID number on the top of your "rounding" schedule – If you want to get paid you'll need to turn in this ID number at the end of the experiment.

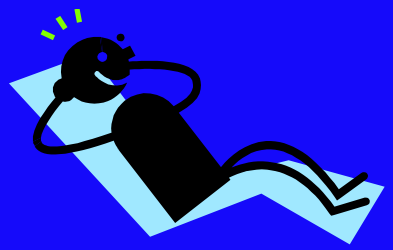
Rooms

- If you are in Rooms 1-8 you'll be rotating in Suites 308 & 310.

- If you are in Rooms 9-16 you'll be rotating through Suites 320 & 322.

Pace

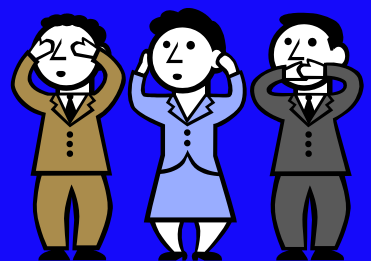
- This is a fast moving event.
- For the first experimental day you'll have 3 min. 45 sec. to review the records and see the patient and 15 sec. to rotate.
- For subsequent days, you'll have 2 min. 45 sec., again with 15 sec. to rotate.
- There will be a start and stop announcement for each patient encounter.
- Monitors in the suites will tell you when you are moving to a new experimental day.



Break

- There will be a 15 min. break around 3 PM. Some of you will spend the break waiting in the hallway – feel free to use the facilities if you need to.
- Others will be asked to spend the break in Room 351 – you may also use the facilities if you need to.
- A proctor will direct you as to which place you should stay during the break.
- *Avoid any discussion of the cases or experiment during the break.*

- <u>After</u> the break you may be given a different order for your rounds to follow.



Questions ?

S2 Appendix [Example of Clinical Information Given to Standardized Patients]

Here is an example of the sketch of clinical information provided to the standardized patients. The table reports a summary of some of the clinical information in the EHR of the patient known as Ashley Barnes in the experiment. It shows the patient's pseudonym, real age, and real surgical procedure. It also reports the experimental day, and real hospital stay day, pain score, pain medication, stool count, and type of diet.

EXAMPLE OF PATIENT CLINICAL INFORMATION GIVEN TO STANDARDIZED PATIENTS

27780512 Barnes, Ashley COLECTOMY +/- COLOSTOMY

This is a 28 year old female with a history of Peutz-Jegher's syndrome that underwent a left colectomy for treatment of a colon mass. She is now %d-days post op.

Experiment Day	1	2	3	4	5	6	7	8	9
Hospital Day	1	2	3	4	5	6	7	8	9
Pain Score	0	0	5	0	3	4	6	0	0
Pain Med								PO	
Stool Count								2	
Diet	NPO	NPO/Solids	Solids	NPO	NPO	NPO	NPO/Clear	Clear/Solids	Solids

S3 Appendix [Scripts Given to Standardized Patients]

Here shows the alternative scripts given to the actor playing "Ashley" (see Appendix 2) in the treatments in which Ashley was Reluctant or Eager to be discharged. The Reluctant and Eager treatments differ in the instructions for patient portrayal in the categories labeled appearance, pain score, activity, bowel function, diet, and social support. Note that, on days earlier than the seventh day in the hospital, reluctant behavior is consistent with the clinical data because Ashley's diet is NPO (nothing by mouth) whereas on later days reluctant behavior might simply convey a general pessimistic attitude and stop serving as an informative signal of her health status.

SCRIPTS FOR RELUCTANT AND EAGER FOR DISCHARGE GIVEN TO STANDARDIZED PATIENTS

	Reluctant to go home	**Eager to go home**
Appearance	Looks disheveled and uncomfortable	Looks well and is asking to leave as soon as MD thinks it's OK
Pain Score	Pain is minimally covered with current pain meds	Pain is tolerable and meds help control the discomfort
Activity	Having difficulty getting out of bed alone and has trouble walking in the hallways	Up and walking in the hallway; no problem getting out of bed
Bowel Function	Is having bowel function but still feels bloated and uncomfortable	Passing gas and moving bowels normally no problem there
Diet	Not interested in any of the food that is brought to them and overall no appetite; has nausea when eats	Tolerating food and has good appetite
Social Support	No one to pick the patient up until much later in the day; worried that he/she will be alone much of the day and therefore may have some problems	Plenty of home support; could leave right now if provider wants to send the patient home

S4 Appendix [Participant Demographics]

PARTICIPANT DEMOGRAPHICS

	Standardized Experiment			Virtual Experiment		
	CDS Supported	Control	p-value	CDS Supported	Control	p-value
Medical School GPA	3.586 {0.256}	3.567 {0.308}	0.833	3.498 {0.278}	3.575 {0.280}	0.349
Undergrad GPA	3.636 {0.231}	3.544 {0.302}	0.298	3.670 {0.240}	3.66 {0.219}	0.877
Female	26.32%	63.16%	0.049	65.22%	45.83%	0.244
Athletic Training	36.84%	15.79%	0.269	34.78%	37.50%	1.000
Musical Training	57.89%	68.42%	0.737	30.43%	58.33%	0.080
Risk Averse	57.89%	52.63%	1.000	56.52%	45.83%	0.564
Nr. of Subjects	19	19		23	24	

Notes. Entries in the ”p-value” columns are for t-test for Medical School GPA and Undergrad GPA and Fisher’s exact test for the other four binary variables (Female, Athletic, Musical and Risk Averse). Standard deviations in curly brackets.