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# Integration of patient experience factors improves readmission prediction

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**Abstract**

Many readmission prediction models have marginal accuracy and are based on clinical and demographic data that exclude patient response data. The objective of this study was to evaluate the accuracy of a 30-day hospital readmission prediction model that incorporates patient response data capturing the patient experience. This was a prospective cohort study of 30-day hospital readmissions. A logistic regression model to predict readmission risk was created using patient responses obtained during interviewer-administered questionnaires as well as demographic and clinical data. Participants (N = 846) were admitted to 2 inpatient adult medicine units at Massachusetts General Hospital from 2012 to 2016. The primary outcome was the accuracy (measured by receiver operating characteristic) of a 30-day readmission risk prediction model. Secondary analyses included a readmission-focused factor analysis of individual versus collective patient experience questions. Of 1754 eligible participants, 846 (48%) were enrolled and 201 (23.8%) had a 30-day readmission. Demographic factors had an accuracy of 0.56 (confidence interval [CI], 0.50–0.62), clinical disease factors had an accuracy of 0.59 (CI, 0.54–0.65), and the patient experience factors had an accuracy of 0.60 (CI, 0.56–0.64). Taken together, their combined accuracy of receiver operating characteristic = 0.78 (CI, 0.74–0.82) was significantly more accurate than these factors were individually. The individual accuracy of patient experience, demographic, and clinical data was relatively poor and consistent with other risk prediction models. The combination of the 3 types of data significantly improved the ability to predict 30-day readmissions. This study suggests that more accurate 30-day readmission risk prediction models can be generated by including information about the patient experience.

**Abbreviation:** CI = confidence interval.

**Keywords:** patient experience, prediction, readmission, risk

## 1. Introduction

There have been innumerate readmission risk prediction tools designed to help understand and prevent 30-day hospital readmissions.[1] Most of these algorithms are built with factors traditionally associated with readmission risk such as clinical comorbidities,[2] lab values,[3] demographics,[4] and prior history of healthcare utilization extracted from claims of electronic health record data.[5] Even so, the impact and efficacy of these readmission tools have generally been limited with modest discriminatory power. While less utilized, factors related to patient experience, often informed by patient response data, have been linked to readmission risk.[6] Specifically, patient perceptions connected to patient satisfaction[5] interactions with care providers,[7] likelihood of readmission,[8] and caring for self post-discharge[9] have all been associated with 30-day readmission but rarely if ever are included in readmission risk algorithms. The importance of patient-related factors has been a recent focus of study. Among others, readmission risk has been assessed in terms of discharge disposition,[10] post-acute care facility usage,[11] timing, particularly as it relates to skilled nursing facilities,[12] and physical and occupational therapy administration.[13] Further, interventions attempting to attenuate readmission have been studied, including the use of community health workers[14,15] and disease-specific interventions.[16] However, patient experience factors remain under-appreciated.

Prior studies have examined the efficacy of validated risk prediction tools. Results have been mixed and patient response data is rarely integrated into readmission risk algorithms. A 2011 systematic review published in JAMA reviewed 26 unique hospital readmission models that were mostly of modest predictive accuracy.[17] The addition of patient-reported data has improved discriminatory power in some models, such as Coleman's early work based on the Medicare Current Beneficiary Survey and Medicare claims,[18] which

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The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

This study was based on prior observational cohorts and all participants provided verbal informed consent prior to this study. All methods were carried out in accordance with guidelines and regulations outlined by the Mass General Brigham Institutional Review Board.

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**Table 1**

**Patient questions. Patients were asked to respond to each of the following 12 questions assessing different aspects of their subjective experience with their care.**

| Number | Questions |
|---|---|
| 1 | How would you rate your overall health? |
| 2 | How would you rate your overall mental or emotional health? |
| 3 | How satisfied are you with the overall care you received/are receiving since you were admitted? |
| 4 | How confident are you about your ability to manage your health issues after leaving the hospital? |
| 5 | How likely would you say you are to be readmitted to the hospital in the next 30 d? |
| 6 | During this hospital stay, how often do doctors listen carefully to you? |
| 7 | During this hospital stay, how often do doctors explain things in a way you could understand? |
| 8 | During this hospital stay, do doctors, nurses or other hospital staff talk with you about whether you will have the help you need when you leave the hospital? |
| 9 | During this hospital stay, do you expect to get information in writing about what symptoms or health problems to look out for after you leave the hospital? |
| 10 | During this hospital stay, how often have staff taken your wishes into account in deciding what you will need when you leave the hospital? |
| 11 | During this hospital stay, how often have staff taken the wishes of your caregivers into account in deciding what you will need when you leave the hospital? |
| 12 | Do you have a good understanding of the things you are responsible for in managing your health after you leave the hospital? |

found patient perceived physical function to be important. A recent systematic review of 41 models derived from electronic health records also found that the majority of the studies had modest to moderate discriminatory power and most models lacked socioeconomic elements or patient response data.[19] A Steventon et al[20] also found that most predictive models demonstrated accuracies of < 0.70. A recent readmission risk study was performed utilizing demographic data, hospitalization history, comorbidities, admission diagnosis, procedures and surgeries, length of stay, and admission and discharge times to predict 30-day readmissions.[21] Their logistic regression model achieved a receiver operating characteristic of 0.71. Frizzel et al[22] used machine learning to predict 30-day readmission in heart failure patients. Their data was obtained from the "American Heart Association Get with the Guidelines Heart Failure" registry and their logistic regression model achieved an receiver operating characteristic of 0.63. A single study did examine patient-related factors including the personal, social, and disease characteristics and achieved an accuracy of 0.73. However, this was for prediction of a return to the emergency department.[23]

In a prior publication of 872 inpatients who were interviewed while hospitalized on internal medicine units in 2012 to 2016,[8] the association of patient experience data generated by verbally administered questionnaires and hospital readmission was explored. Twelve patient experience questions include the following domains: physical and mental health (Q1, Q2), satisfaction with hospital care (Q3), confidence in ability to manage health after discharge (Q4), likelihood of 30-day readmission (Q5), perceptions about patient (Q6, Q7, Q8, Q9, Q10) and caregiver (Q11) interactions with clinical care team members, and patient understanding of how to care for self after discharge (Q12). Two of 12 verbally-administered questions were significantly associated with readmission. In the original study, a logistic regression analysis assessing the individual association of each of the questions, the 2 questions that were found to be associated with readmission were satisfaction with care (Q1) and how well patients felt that doctors listened (Q2).[8]

We hypothesized that the combination of the data generated from the 12 patient experience questions would be more accurate in predicting readmission than the 2 individual questions found to be associated with readmission in the original analysis. We also hypothesized that combining patient response data generated by the 12 patient experience questions with clinical and demographic data in a model would provide novel information regarding the probability of readmission. Here, we performed a factor analysis of the 12 patient experience questions and created a model combining clinical, demographic and patient response data from the 12 patient experience questions to assess readmission risk prediction accuracy.

## 2. Methods

The study design has previously been reported.[8] Inclusion criteria were: age > 18 years; capacity to complete the questionnaire; and English fluency. Exclusion criteria were: health-care proxy invoked status; active incarceration; any planned or scheduled admission. Every effort was made to enroll all eligible patients admitted to study units, however patients were not able to be enrolled if their admission or discharge occurred in a time interval that made patient consent impossible. Out of 1754 eligible patients, 846 were included and 908 were excluded. There were no significant differences in the demographic characteristics, proportion of disease categories or baseline readmission rates of study participants and those that were eligible for the study but not enrolled.

Study participants completed an enrollment questionnaire adapted from a previous survey instrument.[20] This survey instrument was derived from some standard established measures of patient experience for benchmarking as well as validated questions generated by pre-study qualitative interviews with patients and physicians. Questionnaire domains included health-related social needs (e.g., food, housing, transportation needs), perceptions of their physical and mental health, confidence in their ability to care for themselves after discharge, satisfaction with inpatient care, perceived likelihood of readmission, understanding of the care plan, and ability to independently perform activities of daily living. Basic demographics, insurance status, primary diagnosis associated with admission, and major medical and psychiatric comorbidities were collected by chart review. All participants were asked to complete a 30-day post-discharge questionnaire that included questions to assess perceived likelihood of 30-day readmission and confidence in caring for oneself outside the hospital. Trained research coordinators interviewed patients and verbally administered questionnaires on the day of or day prior to discharge after obtaining verbal consent. The patient responses were on a 5-point Likert scale, with 1 being excellent/yes and 5 being poor/no. Patient responses were recorded and stored in a secure online database.[24] The 12 patient experience questions are shown in Table 1.

In addition to patient-reported data, research coordinators completed a structured medical record review to obtain clinical history from the electronic medical record using data captured in the same REDCap database. Abstracted data included age, sex, race, ethnicity, marital status, insurance status, education, primary language spoken, history of homelessness, primary diagnosis, and major medical and psychiatric comorbidities including substance use disorder. Abstracted clinical data (i.e., demographic factors and primary diagnoses from chart review) and patient experience questions were included in the full predictive model. The dependent variable was 30-day readmission.

**Table 2**

**Patient characteristics.**

| Patient characteristics | No readmission (N = 645) N (%) | Readmission (N = 201) N (%) | *P* valuea |
|---|---|---|---|
| Gender (male) | 377 (58.45) | 124 (61.69) | .41 |
| Age category | | | |
| <45 yr | 131 (20.31) | 25 (12.44) | |
| 45–54 yr | 105 (16.28) | 41 (20.40) | |
| 55–64 yr | 131 (20.31) | 49 (24.38) | .1 |
| 65–74 yr | 121 (18.76) | 37 (18.41) | |
| > 74 yr | 157 (24.34) | 49 (24.37) | |
| Race | | | |
| White | 532 (82.48) | 173 (86.07) | |
| Black | 51 (7.91) | 16 (7.96) | .42 |
| Asian | 15 (2.33) | 2 (1.00) | |
| Other/not reported | 47 (7.28) | 10 (4.97) | |
| Hispanic (Yes) | 52 (8.06) | 11 (5.47) | .22 |
| Education | | | |
| HS grad/GED and below | 300 (46.51) | 112 (55.72) | |
| More than high school/GED | 345 (53.49) | 89 (44.28) | .02 |
| Insurance | | | |
| Commercial | 209 (32.40) | 61 (30.35) | |
| Medicare | 305 (47.29) | 94 (46.77) | |
| Medicaid/mass health | 93 (14.42) | 39 (19.40) | .24 |
| Dual eligible | 23 (3.57) | 6 (2.99) | |
| Self-pay | 15 (2.33) | 1 (0.50) | |
| English in primary language (Yes) | 608 (94.26) | 195 (97.01) | .12 |
| Homeless in last year (Yes) | 35 (5.43) | 16 (7.96) | .19 |
| Drug/alcohol abuse history (Yes) | 163 (25.27) | 57 (28.36) | .38 |
| Marital status | | | |
| Married | 232 (35.97) | 68 (33.83) | |
| Single | 240 (37.21) | 75 (37.31) | |
| Divorced/separated | 73 (11.32) | 18 (8.96) | .56 |
| Widowed | 69 (10.70) | 29 (14.43) | |
| Other | 31 (4.80) | 11 (5.47) | |
| Active admission diagnosis | | | |
| Infectious disease | 266 (41.24) | 69 (33.50) | .15 |
| Gastroenterology condition | 168 (26.05) | 67 (32.52) | .1 |
| Respiratory condition | 185 (28.68) | 38 (18.45) | .02 |
| Cardiac condition | 147 (22.79) | 55 (26.70) | .31 |
| Psychiatry | 127 (19.69) | 34 (16.50) | .49 |
| Pain | 62 (9.61) | 19 (9.22) | .73 |
| Neurology | 61 (9.46) | 9 (4.37) | .06 |
| Hemodynamics | 53 (8.21) | 18 (8.74) | .7 |
| Altered mental status | 48 (7.44) | 12 (5.83) | .56 |
| Nephrology diagnosis | 44 (6.82) | 13 (6.31) | .72 |
| Fall | 42 (6.51) | 7 (3.40) | .2 |
| Hematology diagnosis | 19 (2.95) | 6 (2.91) | .73 |
| Trauma | 19 (2.95) | 4 (1.94) | .56 |
| Oncology diagnosis | 16 (2.48) | 9 (4.37) | .15 |
| Medication | 18 (2.79) | 2 (0.97) | .14 |

GED = general educational development test, HS = high school.

[a] Pearson chi-square tests were used to assess differences between readmission status groups for all variables.

We performed 2 analyses, 1 to investigate the relationships between the questions, and a second to assess the ability of the 12 questions to predict readmission. In order to understand how the survey questions related to 1 another, the questions were first clustered by a factor analysis. Factor analysis uses variability in responses to the survey items to model the items as a set of uncorrelated, unobserved latent variables, or "factors." This analysis was done to ascertain whether multiple questions might actually be surveying the same underlying phenomenon. We performed a factor analysis with the "varimax" rotation algorithm, and subsequently interpreted the factors as different aspects of the patient experience. The factor analysis was supplemented by a separate pairwise comparison between questions using Pearson's r to visualize the correlation between responses.

In our second analysis, logistic regression was used to determine the relationship between the patient experience questions and sex and race, and model all independent variables (from the abstracted data) in terms of 30-day readmission. The area under the receiver operating characteristic and its 95% confidence interval (CI) measured the discriminative accuracy of the logistic regression model.[25] Significance was set at $P < .05$. All analysis was conducted in R version 3.4.3 software (R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/).

## 3. Results

The population consisted of 846 patients admitted to 1 of 2 inpatient medical units at Massachusetts General Hospital between January 2012 and January 2016 (See FIGURE/CONSORT diagram).[8] Of the participants, 58% were male and over 63% of participants were 55 years of age or older (Table 2). In the factor analysis, questions 1 and 2 mapped onto 1 dimension, which we called "subjective health" and questions 3 to 12 mapped onto a second dimension, which we called "subjective care." The first dimension relates to how the patient views their own health, and the second dimension relates to how the patient views the quality of medical care they receive within and outside of the hospital. The 2 dimensions were significantly different ($P < .0001$). An examination of the second dimension demonstrated 2 significant sub-dimensions; that we called medical communication and patient and caregiver wishes ($P < .0001$). In the pair-wise correlation analysis with Pearson's r (Table 3), there were 3 sets of correlated questions that were identified: subjective health (Q 1, 2), $R = 0.46$; medical communication (Q 6, 7), $R = 0.53$; and wishes (Q 10, 11), $R = 0.93$. In addition, confidence in 1's ability to care for their health (Q 4) correlated with health and satisfaction (Q 1, 2, 3), and a relationship between medical talk (Q 6, 7, 8) and wishes (Q 10, 11) was seen. In our prior study,[24] we found that patient satisfaction was significantly related to readmission. But satisfaction (Q 3) does not appear to be a unitary factor. Rather, it summarizes several aspects of the patient-perceived readmission and is correlated with subjective health (Q 2), confidence in self-care abilities (Q 4), medical communication (Q 6, 7), and wishes (Q 10, 11). There were no significant differences in the patient responses to questions when stratified by race or sex.

In terms of predicting 30-day readmission (Table 4): demographic factors including age category, sex, race, ethnicity, marital status, insurance status, education, primary language spoken, and history of homelessness together had an accuracy of 0.56 (CI, 0.50–0.62), disease factors had an accuracy of 0.59 (CI, 0.54–0.65), and the 12 patient experience questions had an accuracy was 0.60 (CI, 0.56–0.64). Taken together, their accuracy, 0.78 (CI, 0.74–0.82), was significantly greater ($P < .0001$) than these factors were individually.

## 4. Discussion

Use of a logistic regression model examining the accuracy of readmission risk prediction by combining clinical, demographic and patient experience factors significantly improved the ability to predict 30-day hospital readmission readmissions. In a factor analysis, the individual patient experience questions had limited modeling effect in term of readmission risk prediction. This underlines the importance of adding patient response data focused on patient experience domains to other clinical and demographic factors typically incorporated in readmission risk algorithms.

The overall predictive accuracy of each of the 3 types of patient-related factors (clinical, demographic, patient experience) on their own was of approximately equal magnitude. When combined, these factors resulted in a higher accuracy of 0.78. The combined accuracy of the model with all 3 factors was higher than would be expected if each of the 3 factors were independent and orthogonal. This suggests that each factor adds independent information regarding the likelihood of a patient being readmitted. As such, the patient experience factor not only provides information not contained in the demographic or clinical factors, but also likely informs them as well. Our findings support the idea that readmission is multifactorial. Traditional risk prediction algorithms rely solely on variables procured from the electronic health record, however, the use of patient response data as demonstrated here highlights an important gap in current readmission risk algorithms. By incorporating elements of patient experience and response data, the accuracy of risk prediction improves substantially over comparable models of readmission risk. To our knowledge, this is the first study to demonstrate this type of relationship between these 3 types of patient-related factors and readmission in the same patient cohort.

The importance of incorporating patient response data into hospital readmission risk assessment is by no means an original idea. This is demonstrated by early works of Stewart et al[26] which focused on the impact of physician-patient communication in healthcare outcomes, Beach and colleagues[27] who explored improved healthcare outcomes as driven by the patient-provider relationship, and health care outcomes associated with patient perceptions as presented by Brody and

**Table 4**

**Predictive accuracy. Logistic regression was used to determine the predictive accuracy of different sets of variables: demographic variables (such as age, race, etc.), disease variables related to diagnosis, and the 12 questions. Lastly, all the variables were put into a combined model, which was significantly more accurate than any individual model. Accuracy is assessed using the area under the ROC curve, computed using the c-statistic.**

| Patient-related factors | ROC |
|---|---|
| Demographics | 0.56 (0.50–0.62) † |
| Diseases | 0.59 (0.54–0.65) † |
| Questions | 0.60 (0.56–0.64) † |
| All | 0.78 (0.74–0.82) * |

ROC = receiver operating characteristic.
† = not significant,
*$P < .0001$.

**Table 3**

**Patient question pairwise correlation matrix. Pearson's *r* was used to compute pairwise correlation between the responses to each of the questions. Only the lower half of the pairwise matrix is shown; the upper half is identical the lower but reflected across the diagonal.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.00 | | | | | | | | | | | |
| 2 | **0.46** | 1.00 | | | | | | | | | | |
| 3 | 0.17 | **0.21** | 1.00 | | | | | | | | | |
| 4 | **0.20** | **0.28** | **0.23** | 1.00 | | | | | | | | |
| 5 | 0.14 | 0.10 | 0.10 | 0.13 | 1.00 | | | | | | | |
| 6 | 0.12 | 0.14 | **0.32** | 0.16 | 0.10 | 1.00 | | | | | | |
| 7 | 0.08 | 0.15 | **0.26** | 0.11 | 0.03 | **0.53** | 1.00 | | | | | |
| 8 | 0.08 | 0.03 | 0.11 | 0.10 | 0.02 | **0.23** | 0.19 | 1.00 | | | | |
| 9 | –0.02 | –0.02 | 0.10 | 0.04 | 0.02 | 0.10 | 0.10 | 0.10 | 1.00 | | | |
| 10 | 0.11 | 0.10 | **0.29** | 0.16 | 0.02 | **0.36** | **0.28** | **0.37** | 0.17 | 1.00 | | |
| 11 | 0.10 | 0.11 | **0.29** | 0.14 | 0.04 | **0.35** | **0.31** | **0.34** | 0.17 | **0.93** | 1.00 | |
| 12 | 0.12 | 0.09 | 0.12 | 0.10 | 0.07 | 0.14 | 0.10 | 0.06 | 0.02 | 0.11 | 0.10 | 1.00 |

associates.[28] More recently, Chandra and colleagues[29] developed and validated a readmission risk model among patients being discharged to skilled nursing facilities in order to risk stratify patients at the time of hospital discharge. This practical application or readmission risk prediction in real time as a bridge to tailoring resources and interventions to prevent 30-day readmissions should be the goal writ large for institutions dedicated to quality. As clearly outlined in the Institute of Medicine's Crossing the Quality Chasm and, the Institute for Healthcare Improvement's Triple Aim,[30] approaches that place patients at the center of their care are best poised to improve patient experience and patient outcomes. Despite this, the review of more recent literature describing the use and composition of current readmission risk algorithms shows a general failure to embrace this recommendation. One reason for this was rooted in the complexity of parsing a myriad of individual and systemic factors to generate useful and functional readmission tools.[31] This has now in some ways been addressed with increasing popularity and availability of predictive modeling techniques including advanced machine learning methods, decision trees, and deep learning which have joined the historical methods of logistic regression. Admittedly, another barrier to incorporating this kind of data is the limited availability of these types of data in electronic medical records. Only in more recent years have institutions begun to start incorporating patient response data related to experience or even social determinants of health.[32] Given the extensive resources dedicated to clinical outcomes, dedicating even a fraction of this attention to the collection and integration of patient experience data would be an impactful first step in our more rigorous understanding the patient experience with respect to hospital readmissions and ways to positively impact patient outcomes.

The pairwise comparisons within the factor analysis did demonstrate both some expected and unexpected findings. Surprisingly, patient satisfaction though identified in the original study as significantly related to readmission, was not found to have a unitary or direct relationship here. In addition, here we found that satisfaction was a composite of patient domains for perceived health, medical communication, and wishes which were individually associated with readmission risk. This is supported by several studies assessing satisfaction as a complex metric influenced by patient demographics and care interactions.[33] Exploratory factor analysis is considered "one of the strongest approaches for assessing construct validity [of an instrument],"[34] and has been previously utilized to assess clusters of survey questions relating to readmission prediction from a health IT survey[35] as well as to composite questions from the consumer assessment of healthcare providers & systems hospital survey of patient and hospital experience factors.[36] Further, there are a handful of studies that have generated risk prediction models inclusive of some element of patient response data via self-reported patient questionnaires or even natural language processing.[37] However, to the best of our knowledge this is the first study to use factor analysis to identify shared or overlapped themes of qualitative interview or survey questions that take into account the patient experience when predicting readmission.

We believe that the best approach to predicting which patients are at a high risk of readmission within 30 days goes beyond electronic health record data to include factors that can underline important patient experience characteristics, offering context to the patient clinical and demographic domains. Depending on individual patient scenarios, this improved accuracy can provide additional key and actionable information for hospital discharge teams. In doing so, this type of patient-centered data can also further the goal of achieving value-based health care with higher quality and at lower cost.

There are several potential limitations to this study. We were unable to completely exclude participation bias because questionnaire responses may not have been collected from patients that were sickest and unable to complete the survey. The results were restricted to patients who were able to complete the survey. Another limitation was that the study was conducted on a single medical service among English-speaking patients. The strengths of the study include the focus on patient responses to novel questions relevant to readmission, the size of the study population, and the spectrum of diagnoses from a sample of general medicine patients. While clinical prediction models can demonstrate bias due to random effects in specific patient populations seen in a particular hospital setting. Further research is needed to assess external validity in other populations and settings.

## 5. Conclusions

In conclusion, the individual questions about patient experience did not augment readmission risk prediction. The combination of all 12 patient experience questions was associated with readmission prediction. Furthermore, we found that combining patient experience factors, in conjunction with demographic and clinical factors in a logistic regression model, increased predictive accuracy. As healthcare systems continue to address readmissions using process improvement methods and multi-disciplinary patient-centered interventions, incorporation of patient experience factors will become increasingly central. While there has been a great deal of interest in predicting readmission using administrative data, this study provides evidence that demographic and clinical data should be accompanied by data describing the patient perspective if the goal of effectively predicting readmissions and ultimately impacting readmission rates is to be achieved.

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## Author contributions

**Conceptualization:** Harry M. Burke, Jocelyn Carter.
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