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Patient Heal Thyself: Reducing Hospital Readmissions with Technology-Enabled Continuity of Care and Patient Activation

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Patients' skills, knowledge, and motivation to actively engage in their health care are assessed with the patient activation measure (PAM). The literature on the role of PAM, when patient counseling is coupled with a technology enabled continuity of care intervention, is scant. We model the patient–health care provider feedback loop and learning through error corrections to explore the relations between continuity of care, PAM and patient readmissions. We test this model using data from a randomized, controlled field experiment. Our data show a direct effect of technology-enabled continuity of care, together with its interaction with PAM, reduces readmissions over the base case without technology enabled continuity of care. Using exploratory analysis, we further show how a machine learning algorithm can be used to predict PAM, that can potentially furnish health care providers with useful information during the process of supporting their patients.

Key words: behavioral operations; controlled studies; machine learning; patient activation; technology-enabled continuity of care
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1. Introduction

Chronic disease patients incur 86% of US health care costs (Gerteis et al. 2014). Effective management of chronic diseases requires both appropriate clinical care and patient involvement, including (but not limited to) proper diet, exercise, compliance with treatment protocols, and tracking and managing symptoms (Bodenheimer et al. 2002, Wagner et al. 1996). Patients' engagement with their own care is deemed so important that it has been labeled the "blockbuster drug of the century" (Chase 2012). Patient engagement has been studied broadly to either encompass health outcomes or to examine how health care systems are designed and governed (Carman et al. 2013, Hibbard and Greene 2013). Within the sphere of engagement research, patient activation describes a patient's abilities and inclination to manage their care (Hibbard et al. 2005).

Patients with high activation make better health-related decisions and have better health outcomes than patients with low activation; this positive association holds across a wide variety of patient diagnoses and ethnicities (Alegría et al. 2009, Aung et al. 2015, Greene et al. 2015, Hendriks and Rademakers 2014, Marshall et al. 2013, Shively et al. 2013). This research

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stream builds on a validated and reliable questionnaire instrument grounded in behavioral science: the patient activation measure (PAM, see Hibbard et al. 2005 for validation details). This instrument scores individuals (on a theoretical 0–100 scale) and classifies them into one of four levels: (i) May not believe that the patient role is important in treatment outcomes, "My doctor is in charge" attitude; (ii) Lacks confidence and knowledge to take action, "I could be doing more" attitude; (iii) Is starting to take action, "I'm part of my healthcare team" attitude; (iv) Has made many behavior changes, but may struggle to maintain changes under stress; "I'm my own best advocate" attitude.

In addition to the important link between higher PAM scores and better health-related decisions, knowing a patient's PAM score is important because this allows health care providers to improve their responsiveness to the patient, and overall continuity of care (Dixon et al. 2009, Rathert et al. 2012, Shively et al. 2013). Continuity of care–defined as the degree to which a patient experiences individualized care over time, that is "coherent and connected and consistent with the patient's medical needs and personal context" (Haggerty et al. 2003, p. 1221)—is a key element in supporting patients with chronic disease (Holman and Lorig 2004, Wagner et al. 2001). Such care positively influences patients' patient activation (Turner et al. 2015, Wolever and Dreusicke 2016). Of particular interest within this stream of work is the technology enabled continuity of care (TECC), and health care providers' ability to learn (Tucker and Edmondson 2003) wherein providers remotely, coherently and consistently provide individualized care and improve patient's health outcomes. To our knowledge, only one other study uses a remote continuity of care solution to influence activation—this study used telemonitoring and periodic telephone calls to influence activation and health care outcomes in diabetic patients (Shane-McWhorter et al. 2015). This study differs from their study in terms of the type of metrics tracked (metrics relevant to chronic obstructive pulmonary disease (COPD) and congestive heart failure (CHF) as opposed to diabetes), frequency of providing feedback to patients, timeframe of study, and inclusion of readmissions data. Moreover, extant studies do not assess the predictability of PAM scores. Our formulation explores learning through error correction theory, where health care providers can better understand patients' needs based on patient feedback signals and thus better provide patient care. In doing so, we examine the following question: *How are TECC, patient activation, and hospital readmissions related?*

We explore this question through a field study of TECC implementations with CHF and COPD patients from nine hospitals. In assessing patients' PAM scores and hospital readmissions data, we investigate the relationship between TECC, PAM, and hospital readmissions using regression analysis. Our data show a direct effect of TECC, together with its interaction with PAM, reduces readmissions over the base case without TECC. We explore how TECC may influence both PAM and readmissions, and find a nuanced relationship, given that many factors can affect PAM. Given these results, we also conduct exploratory data analysis using a machine-learning algorithm to predict PAM, and to inform follow on predictive analytics research in this context.

2. Hypotheses Development

Patients with a chronic disease must continuously manage their condition (Tsai et al. 2005, Wagner et al. 2001). For example, patients with CHF can best manage their condition through self-care actions such as consistently taking their prescribed medications, following a low salt diet, reaching a healthy weight and exercising regularly (Artinian et al. 2002, Cameron et al. 2009). Although these tasks may seem straightforward, choosing these actions consistently is notoriously difficult (Dickson et al. 2013, Wolever and Dreusicke 2016). Consistent and repeated actions not only allow the patients to better understand their needs, but also to enable health care providers to learn and adapt to the patient's unique circumstances.

In terms of patient actions, extant work shows that personalized feedback to patients, such as is provided in continuity of care, provides support for patients to gradually gain the necessary skills, resolve, and confidence to incorporate changes (Parry et al. 2006, Wolever and Dreusicke 2016). This feedback is an important element of supporting patients with chronic disease (Holman and Lorig 2004, Wagner et al. 2001). In other words, continuity of care enables health care providers to consistently and repeatedly not only interact with patients, but also to learn from patients' decisions and outcomes to update and refine support to patients. In this study, we posit that this continuity of care can be provided remotely, using TECC. For this to be effective, the health care provision system must learn about and adapt to patients.

Argyris defines learning as "the detection and correction of errors" (1976, p. 365). Argyris further explains this mechanism by saying: "The detection and correction of error produces learning and the lack of either or both inhibits learning." This lays the groundwork for a learning loop, which has been described as decision-makers changing behaviors based on an observed outcome differing from an expected outcome (error detection), leading to a change in action believed to better meet the expected,

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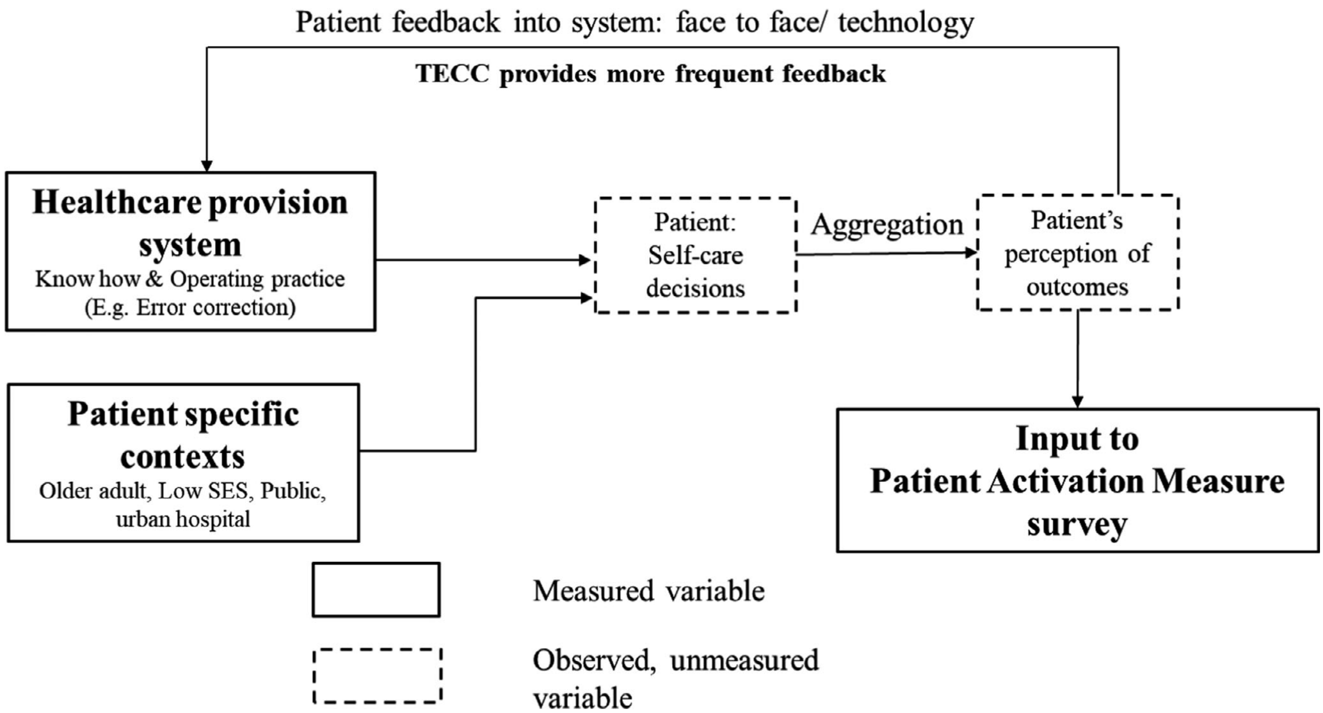
Figure 1 Error Correction Framework



or desired outcome (error correction) (Argyris and Schon 1974).

Figure 1 illustrates this loop, the basis for our theory on health care providers' primary actions: error correction to adapt and improve diagnosis. The health care provision system, which includes doctors, nurses, family and friends, and other information sources, supplies health care information and recommendations which patients consider when making self-care decisions (Carman et al. 2013, Coulter et al. 2008). These recommendations may include diet suggestions, medication scheduling, and methods to reduce stress and lower blood pressure.

Once a patient receives this information, the patient then makes self-care decisions, such as food choices and whether or not to take medication as prescribed. After a patient makes a self-care decision, that patient then perceives (accurately or not) the result of the decision(s). Although the thousands of decisions a patient makes over weeks may vary slightly, a patient's level of activation—their level of knowledge and motivation around their care—informs his/her decisions. Because patients make thousands of microdecisions over time that are not tracked (e.g., breakfast and exercise choices for a certain day), this research instead measures patients' aggregate activation level that has been shown to be highly correlated with patient care decisions and health outcomes (Alegría et al. 2009, Aung et al. 2015, Greene et al. 2015, Hendriks and Rademakers 2014, Marshall et al. 2013, Shively et al. 2013). Therefore, the model in this research incorporates two latent (i.e., observed but not measured) variables—patient self-care decisions and patient perceptions of outcome—that influence the PAM. Such aggregation of decisions over time is customary practice for learning loops representing continuous decision variables (see for instance, an analysis of transactional memory systems, Anderson and Lewis 2014).

Patients provide aggregate feedback into the health care provision system that allows health care providers to learn from the patients and refine their recommendations or support to an individual patient. This feedback from patient to health care provider and back can occur through face-to-face appointments or digital communications (Hu et al. 2018). Regardless of mode, this feedback enables health care providers to improve support to specific individuals (Street et al. 2009) and focus on challenges specific to a patient. These health care provision system inputs function as an error correction term. In our system, we propose that if a patient shares observed outcomes that are undesirable with the health care provision system, that system will provide advice to "correct the error" in single loop learning speak. More specifically, TECC patients provide daily updates to the health care provision system and receive frequent feedback from that system. (See Appendix S1, Sections A & C for more details.) This research theorizes that this frequent feedback enables better error correction, leading to patients with higher patient activation. Conversely, patients without TECC receive significantly less frequent feedback. To be clear,

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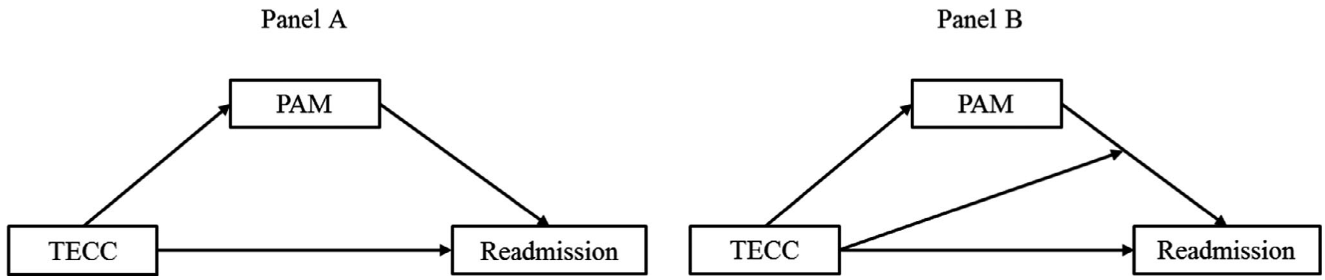
Figure 2 Mediation and Moderated Mediation Models



patients without TECC are encouraged to see their primary care physician (standard care after discharge from the hospital), but do not have daily interaction with the health care provision system. Thus, patients without TECC have fewer opportunities for the health care provision system to learn from the patients regarding how to better support them, thus leading to lower PAM levels. Thus, we present our first hypothesis:

H1. *TECC is positively associated with PAM.*

In addition to a positive relationship with PAM, theory suggests that TECC is negatively associated with patient readmissions. The nascent stream of continuity of care research supports a positive relationship between continuity of care and health outcomes, including fewer hospital admissions (Cheng et al. 2010, Senot 2019, Van Servellen et al. 2006, Van Walraven et al. 2010). Similarly, when continuity of care is delivered virtually, it continues to provide similar benefits to face to face delivery. The increased feedback from the patients increases the probability of a care provider seeing a signal of deteriorating health and intervening before it becomes more serious. That is, patients use TECC daily to provide feedback (blood pressure, weight, answers to questions regarding the patient's conditions, etc.). Even though care providers are not scheduled to speak with a given patient every day, the care providers monitor patient responses, and the system alerts the care providers if a signal is out of the ordinary (e.g., a patient's weight increased 5l bs in 1 day, indicating water retention). If a response is out of the ordinary or concerning, a care provider contacts the patient to find out more and work with the patient and the patient's physician on next steps, including an action such as setting up a same day appointment to see the physician, which may result in medication changes, or other preventative measures. Because of this ability to see early warning signs and intervene before a patient's health deteriorates, we propose:

H2A. *TECC is negatively associated with readmissions.*

In addition to asserting that TECC is negatively related with readmissions, we also argue that PAM mediates this relationship. That is, health care providers are interested in raising patient activation because it is a proximal variable to measure overall health and health care costs (Greene and Hibbard 2012, Greene et al. 2015). Thus, we choose to examine the relationship between TECC, patient activation, and hospital readmissions. More specifically, we posit that PAM mediates the relationship between TECC and readmissions (Figure 2, Panel A).

In studies that do not incorporate TECC, patients with higher activation demonstrate better self-care than those with lower activation (Begum et al. 2011, Fowles et al. 2009, Graffigna et al. 2017, Greene and Hibbard 2012, Harvey et al. 2012, Hibbard et al. 2015, Zimbudzi et al. 2017). This better self-care generally leads to better health (Greene and Hibbard 2012, Greene et al. 2015), and fewer hospital admissions (Begum et al. 2011, Hibbard et al. 2009, Mitchell et al. 2014). We posit TECC increases patient activation, which improves patient self-care, and health, which in turn reduces readmissions—a patient admitted to a hospital within 30 days of discharge from a hospital. Therefore, we propose patient activation mediates a relationship between TECC intervention and reduced readmissions:

H2B. *PAM mediates the relationship between TECC and readmissions such that PAM is negatively associated with readmissions.*

While increased patient activation is a desirable goal, the previous hypothesis assumes equivalence across all patients. That is, if two persons have identical physiological conditions but one has a higher activation, while the other has a lower activation, the patient with lower activation has a higher probability of readmission. However, patients seldom have identical physiological conditions and physical condition can influence activation. Hence, the relationship between TECC, PAM, and readmissions may be more complex than simple mediation.

Research on COPD and CHF patients shows that those with more serious and/or immediate health problems are more likely to be more actively involved in their self-care (Cameron et al. 2009, Riegel et al.

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2007, Rockwell and Riegel 2001, Warwick et al. 2010). An explanation for this phenomenon is that less sick patients are not imminently facing severe consequences; self-care changes, such as changing diet and making time and effort for exercise are difficult and often prompted by immediate needs (Bentley et al. 2005, Dickson and Riegel 2009). In other words, while higher PAM levels are desirable, many different factors lead patients to higher PAM levels, including worsening underlying medical conditions, which may lead to hospital readmissions.

However, if patients have similar motivation levels, as measured by PAM, the patients with TECC may be better equipped through the coaching advantage that TECC supplies (Gawande 2011, Olsen and Nesbitt 2010, Parry et al. 2006). Therefore, the effect of PAM on readmissions is not simple; it is also conditional on whether or not the patient has TECC, modeled as a moderating factor. This is referred to as a moderated mediation model (Hayes 2013) and illustrated in Panel B of Figure 2, and is set up as a competing hypothesis to H2b. We test this via the next hypothesis:

H2C. *TECC moderates the mediation effect hypothesized in H2b. That is, the interaction between TECC and PAM is negatively associated with readmissions.*

3. Field Study

3.1. Design of Experiment

These hypotheses are tested using a controlled, randomized experiment. This experiment focuses on patients discharged from nine hospitals in the greater Indianapolis, Indiana metropolitan and surrounding areas who had a primary discharge diagnosis of CHF and/or COPD — common chronic diseases that require significant patient self-care (Artinian et al. 2002, Bourbeau et al. 2003) and reflect high (>20%) hospital readmission rates (Jencks et al. 2009). After recruiting and randomizing patients, the study had 95 control patients and 74 intervention patients. (See Appendix S1, Section A for more details.) There are no statistical differences between the control group and the intervention group in regard to age, race, or health status (See Appendix S1, Table A.1). The intervention group used TECC for 30 days. Both groups received routine follow-up care after hospital discharge and were asked to answer the PAM instrument from 30 to 60 days post discharge.

Continuity of care can be segmented into three broad areas of continuity: informational, managerial, and relational (Haggerty et al. 2003). When care providers (i) track and share data related to a specific patient and their condition (informational continuity); (ii) use a consistent and appropriate approach to caring for a person and their condition (managerial continuity) and (iii) continue to care for the same patients over time (interpersonal continuity), better health outcomes are more likely than when only one continuity exists (Guthrie et al. 2008, Van Servellen et al. 2006). Thus, all three types of continuity of care were included with TECC.

In this experiment, TECC includes sharing objective information (for example, blood pressure, weight, if the patient was experiencing swelling) daily through a telemonitoring device that electronically maintains this data, thus providing informational continuity. Periodic video conference calls with a health care provider, (3 the first week, 2 the second week, 1 the third week) conducted using telemonitoring technology provided both managerial and interpersonal continuity. Because the same health care provider called a given patient, there was interpersonal continuity. The health care provider and patient established a therapeutic relationship, so they better understood and trusted each other. These teleconferences enabled the health care providers to assess the patients' status; during the teleconferences, the health care provider reconciled the medication (asking the patient to show the health care provider the medications they had, comparing them to what they should have, making sure the patient knows how and when to take them) and addressed patients' concerns during the recovery period. The technology enhanced the productivity of these calls because health care providers could incorporate both the passive objective data (e.g., vital signs and health questionnaire responses) and the patient's facial expressions, breathing and other body language. For example, if a patient's data showed an increase in blood pressure, the health care provider might ask what the patient has been eating and help the patient understand how eating a hot dog directly affected blood pressure. The health care provider followed a consistent protocol, thus enabling managerial continuity. For details of the protocol, see sections A, B, and C in Appendix S1.

3.2. Dataset

The following information was collected about study patients: patient activation, number of hospital readmissions, and insurance type. The details are described next, along with how these data were used to operationalize variables.

3.2.1. Independent and Dependent Variables. To assess patient activation, we used the 13-question PAM survey, a validated, uni-dimensional, proprietary instrument measuring patient activation (Hibbard et al. 2005). The survey includes questions on patients' self-perceived ability and motivation to care for their own health. Patients were asked to complete

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this survey by phone from 30 to 60 days post discharge. A project manager attempted calling the patient five times without making contact before classifying a patient as a non-respondent.

The Indiana Health Information Exchange provided readmission data for study patients. That is, the Exchange provided the research team with data regarding whether any of the patients were readmitted or not for any cause within 30 days after hospital discharge. The Indiana Health Information Exchange tracks these data for all hospitals in the greater Indianapolis area, so the Exchange could say if a patient was readmitted or not into any area hospital. We chose the 30 day limit because this is an increasingly important health care operation metric (Helm et al. 2015, Senot et al. 2016) and under the 2010 Patient Protection and Affordable Care Act, the US government (through CMS) levies penalties for hospitals with high readmission rates (PPACA 2010). With this, patients were either readmitted to a hospital (1) or not (0).

We operationalize TECC as a dichotomous variable with TECC classified as "1" for patients provided TECC and "−1" for patients not provided TECC.

3.2.2. Control Variables. We control for a few factors in our analysis: whether or not the patient is an older adult (aged 65 or over), whether or not the patient has low socioeconomic status, and whether or not the patient presented at a public, urban hospital. We next explain how we operationalized these factors and reasons for including them in the analysis.

Research offers mixed findings regarding how age affects patients' health habits. Some research shows older adults change their health habits at the same rate (or faster) as younger adults, and this can be explained by older adults' low tolerance for risk and their nearness to poor health habits' consequences (Fries et al. 1992, Leigh et al. 1992). Other research shows that older patients are less likely to change habits, including health-related habits, than younger patients (Cole et al. 2008, Grandes et al. 2008). Given that a key requirement for self-care is the ability to form new habits (e.g., diet, exercise), and shed old habits (e.g., smoking, sedentary lifestyle), the range of changes needed is broad. Thus, we argue that older adult patients are less likely to change their behavior to create these new habits than younger patients.

Patients in our sample were treated in one of nine different hospitals, including a public, urban hospital. We use this variable because public, urban hospitals tend to serve as a safety-net for low-income patients, tend to have fiscal pressures and be located in high-crime neighborhoods (Gourevitch et al. 2008, Regenstein et al. 2005). Patients likely to present at these hospitals tend to delay seeking care or not seek care altogether, because of a variety of challenges (Rask et al. 1994). Not only do these patients typically have health insurance with lower levels of coverage, but they also usually have fewer sick-day benefits to seek medical care and fewer daycare options for children and rely more heavily on public transportation (Rask et al. 1994). Thus, patients presenting at these hospitals overcome barriers to seek care and must either be in dire need of health care and/or particularly motivated to get better. The health belief model posits that for patients to make a change in their health habits, they must feel a need to take action and feel threatened by their current health habits (Rosenstock et al. 1988). Patients presenting at urban, public hospitals feel threatened enough to seek care, and thus may be more motivated to be activated than an equivalent patient at another hospital. Similarly, patients with low socio-economic status have similar challenges and similar motivation.

We infer these patient characteristics (age status, hospital attended, socio-economic status) through patient insurance type. We assign "older adult" status, that is, age 65+, ("1") for patients with Medicare insurance and "younger adult" status ("−1") for those without Medicare. We indicate whether patients were treated at this urban hospital ("1") or not ("−1") by patients' insurance type—this hospital was the only one of the nine that accepted a hospital specific insurance plan. We classify our study subjects based on socioeconomic status and assume that patients with Medicaid have low socioeconomic status ("1") and those with other insurance types do not ("−1"). (Many patients have several insurance carriers: a patient can be classified as both low socio-economic status and age 65+ status by having both Medicaid and Medicare.) For a patient with an unknown characteristic (i.e., we do not have information regarding if they are an older adult or not), we used a "0" for that control variable.

4. Model Specification

Using regression analysis, we test our hypotheses, which propose interrelationships between TECC, PAM, and our outcome variable, readmissions, along with the three control variables described earlier. Consistent with mediation model norms (Hayes 2013, Wiedemann et al. 2009), we deploy bootstrapping to develop 95% confidence intervals around the key estimate to reject the null hypotheses that these estimates can take a zero value.

We first test H1, that is, the relationship between TECC and PAM (our proposed mediator) using a linear regression model (Model 1). We find support for H1 if β_{11} is positive and significantly different from zero.

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We proposed that TECC, PAM, and readmissions are connected either through a mediation model (Model 2—Hypothesis 2b) or a moderated mediated model (Model 3—Hypothesis 2c). We analyze the fit statistics of these two models to determine which of the models better fits our empirical data, with a higher Wald χ^2 stat and higher McFadden R^2 stat showing the best support.

In both Model 2 and 3, we can assess whether or not TECC is directly associated with reduced readmissions (Hypothesis 2a), by evaluating whether or not β_{21} and β_{31}, respectively, are negative and significant. We wait to determine whether to look at β_{21} or β_{31} based on whether Model 2 or 3 is the better fitting model. We specify models 1, 2, and 3 in the following way:

Model 1: PAM = β_{10} + β_{11}TECC + β_{12}LowSES + β_{13}OlderAdult + β_{14}Urban + e_1
Model 2: ln (Readmission odds) = β_{20} + β_{21}TECC + β_{22}PAM + β_{23}LowSES + β_{24}OlderAdult + β_{25}Urban
Model 3: ln (Readmission odds) = β_{30} + β_{31}TECC + β_{32}PAM + β_{33}PAM × TECC + β_{34}LowSES + β_{35}OlderAdult + β_{36}Urbanwhere PAM is the measured activation, TECC, LowSES, OlderAdult, and Urban are binary variables, and e_1 is an error term.

5. Results

We present summary statistics for our patients in Table 1. This includes the control variable distribution for patients with and without TECC. In addition, Table 1 displays the average patient activation for each group and the number of hospital readmissions within 30 days.

To test the hypotheses, we analyze the regression specifications in Equations (1), (2), and (3) using bootstrap analysis (1000 runs) and report the results as a 95% confidence interval. The null hypothesis in each case stipulates that the regression coefficients equal 0, and if our confidence intervals do not contain 0, then we find support for the hypothesis.

Regressing PAM on TECC, Table 2 shows a positive and significant relationship between TECC and PAM (β_{11} = 6.714, 95% confidence interval: 3.354, 9.717), supporting Hypothesis 1: TECC is positively associated with PAM.

Next, we evaluate Models 2 and 3 to assess if TECC, PAM, and readmissions are best modeled as a mediation or as a moderated mediation, respectively. Looking at Table 2, results for models 2 and 3, we see reasonable fits (Model 2: Wald χ^2 stat = 3.65, McFadden adjusted R^2 = 0.18; Model 3: Wald χ^2 stat = 3.63, McFadden adjusted R^2 = 0.19). Given the marginally higher R^2 value for Model 3, along with TECC, PAM, and their interaction all being significant, we select Model 3 (moderated mediation model) as the best model and hence, we use that model for our results.

To evaluate Hypothesis 2a, we look to β_{31} in Model 3. TECC has a negative and significant coefficient (β_{31} = −0.672, 95% confidence interval: −0.889, −0.435). Thus, our data supports Hypotheses 2a: TECC is negatively associated with readmissions.

Hypothesis 2b proposed that PAM mediates the relationship between TECC and readmissions. However, we compared Model 3 and 2 to determine if the relationship is better characterized by a mediation relationship or a moderated mediation relationship. Because the moderated mediation relationship better characterizes the relationship, Hypothesis 2b is not supported.

Hypothesis 2c proposes a moderated mediation model, with TECC impacting the effect of PAM on readmissions. Given the overall fit is adequate, as discussed earlier, we can examine the interaction effect. The interaction effect of TECC and PAM is significant and positive (β_{33} = 0.002, 95% confidence interval: 0.002, 0.006), meaning TECC has different impacts for patients with different PAM values, thus showing support for a mediated moderation model, part of Hypothesis 2c. However, Hypothesis 2c specifies the interaction between TECC and PAM is negatively associated with readmissions, vs. results show the interaction is positively associated with readmissions. Thus, we find support for a moderated-mediated

Table 1 Summary Statistics for Analysis (*n* = 118)

	Patients with TECC *N* = 69			Patients without TECC *N* = 49		
Average PAM	66.9			56.1		
	Yes	No	Unknown	Yes	No	Unknown
Readmitted to hospital	3	66	0	5	44	0
Older adult	30	2	37	20	0	29
Urban, public hospital	9	45	15	8	36	5
Low socioeconomic status	22	2	45	17	0	32

Note: PAM, patient activation measure; TECC, technology enabled continuity of care.

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Table 2 Regression Results—95% Confidence Interval Shown in Parentheses

	Model 1 Dependent variable: PAM	Model 2 Dependent variable: readmissions	Model 3 Dependent variable: readmissions
Intercept	58.740*	−4.516*	−4.474*
	(53.709, 63.831)	(−4.640, −4.251)	(−4.629, −4.185)
Hypotheses variables			
TECC	6.714*	−0.516*	−0.672*
	(3.354, 9.717)	(−0.568, −0.471)	(−0.889, −0.435)
PAM		0.034*	0.030*
		(0.031, 0.037)	(0.030, 0.037)
TECC × PAM			0.002*
			(0.002, 0.006)
Control variables			
LowSES	4.369	−1.201*	−1.215*
	(−1.835, 11.116)	(−1.308, −1.099)	(−1.319, −1.108)
Older Adult	−0.848	−0.518*	−0.505*
	(−7.021, 5.140)	(−0.615, −0.422)	(−0.597, −0.407)
Public, urban hospital	−2.154	−0.355*	−0.336*
	(−6.643,2.634)	(−0.424, −0.271)	(−0.408, −0.258)
Fit stats			
Wald χ^2 statistic	10.82	3.65	3.63
McFadden-adjusted R^2	0.35	0.18	0.19

Note: *Significant at the 0.05 level; n = 118. PAM, patient activation measure; TECC, technology enabled continuity of care.

model, but not in the hypothesized direction, and hence we find partial support for Hypothesis 2c.

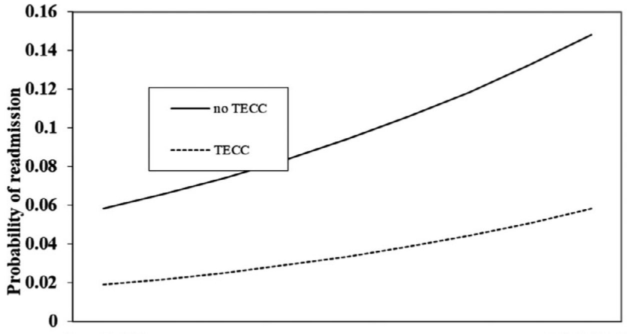
6. Discussion

6.1. Nuanced Relationships

Our analysis supports Hypothesis 1, linking TECC positively to PAM. Past research leads us to believe that these higher levels of PAM would lead to better health outcomes, such as reduced readmissions (Greene and Hibbard 2012, Mitchell et al. 2014), supporting a mediation model. We show support for a moderated mediation model, and our results show that PAM is positively associated with readmissions, both with and without TECC.

To better understand this nuanced relationship based on the moderated mediation model, in Figure 3 we graph the odds of readmissions at low (−1 SD) and high (+1 SD) PAM, with and without TECC. The figure shows: (i) TECC patients have lower odds of readmission than those without TECC, and (ii) an increasing probability of readmission as PAM increases. While the first conclusion is consistent with our theoretical reasoning, the second conclusion showing that higher PAM are associated with higher readmissions could be consistent with CHF and COPD literature in the following way: we have a sick patient population (all of our patients were hospitalized for either CHF or COPD). Furthermore, our patient population had, on average, a Charlson comorbidity index of at least 3 (see Appendix S1, Table A.1) indicating patients at high risk (Charlson et al. 1987). COPD and CHF literature shows that those with more serious and/or immediate health problems are more likely to be more actively engaged in their health (Cameron et al. 2009, Rockwell and Riegel 2001, Warwick et al. 2010). Thus, there are two competing factors driving patients towards higher patient activation: a desire to take charge of their health, and worsening symptoms. Our Hypothesis 1 result shows a positive relationship between TECC and patient activation which indicates TECC can help those that are interested in increasing patient activation. On the other hand, patients with the highest probability of being readmitted to the hospital (the sickest) also have the most immediate drive to get better, and so are highly motivated. Hence, our results could be explained as TECC can help improve patient activation and patient activation drives explanation of readmissions. However, the relationship from TECC to PAM to readmissions is complex, as some of the

Figure 3 Impact of Patient Activation Measure (PAM) and Technology Enabled Continuity of Care (TECC) on Probability of Readmission



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sickest patients are most likely to actively work to increase patient activation. Even though the sickest patients are more activated, they are also more likely to be readmitted because of their complications. Alternatively, risk-averse care providers could be causing these results. That is, high PAM patients may be more likely to call a doctor or nurse when they see a difference in their body. This difference may or may not be indicative of a critical issue, but a risk-averse care provider may be more likely to readmit these vigilant patients.

Another nuanced aspect is the impact of TECC at different values of PAM. Because the interaction term of PAM $\times$ TECC is significant (see Table 2, Model 3), the impact of TECC is different at low values vs. high values of PAM. Figure 3 shows with TECC, the probability of readmission increases from 0.02 (PAM = −1 SD) to 0.06 (PAM = +1 SD), meaning an increase of 0.04 over 2 standard deviations. Similarly, with no TECC, the probability of readmission increases from 0.06 to 0.15, meaning an increase of 0.09 over 2 standard deviations. This shows with TECC, patients increase their probability of readmission at a slower rate than without TECC. This can be translated to mean that actively engaged patients see even better outcomes when they work with health care provider coaches. It shows the complementary nature of an activated patient, receptive to both health care provider feedback and to a changed mindset.

6.2. Exploratory Analysis

As mentioned at the outset, aside from the hypotheses examined in this study, the literature does not address how a health care provider might predict a patient's activation. For instance, can a health care provider predict higher patient activation for patients with TECC? Hence, after testing our hypotheses, we chose to explore whether our data provide any preliminary insights on making predictions about a patient's activation based on their characteristics and TECC. The previous analysis to test the hypotheses used the PAM data on a 100-point scale. For this exploratory work, we are less interested in an exact amount of activation and more interested in whether patients had low activation, medium low activation, medium high activation or high activation (Patient Activation Levels 1 through 4, respectively), so we focus on predicting patients into these categories. The cut off points for these PAM scores set up defined categories, per the Patient Activation scale (Hibbard et al. 2005).

To explore predictive ability, we first define the classification boundaries and then explore prediction options for each boundary. Since the PAM scale is cumulative (Hibbard et al. 2005), we examined three classification boundaries: whether the 100-point patient score was in level 1 vs. levels 2, 3, and 4; levels 1 and 2 vs. levels 3 and 4; and levels 1, 2, and 3 vs. level 4. With these classification boundaries, we run predictions using two methodologies—a traditional logistic regression and a linear support vector machine (SVM) (Anderson et al. 2015). We compare these methods in sections D and E in Appendix S1. As shown in Tables E.2A and E.2B in Appendix S1, using prediction error as our metric, SVM provides a better solution than logistic regression. Hence, we conclude SVM is the better choice to predict patient activation level.

Support vector machine separates data into two classes by constructing a hyperplane using a set of training data so that when new data is added, the SVM characterizes the data into one of the two classes. A successful hyperplane has a larger margin between the hyperplane and nearest training set data point, as a larger margin means the training points associated with each class are further apart, resulting in fewer misclassifications (Cortes and Vapnik 1995).

We next explain the type of SVM and training set size we use. Since the total errors are larger with logistic regressions vs. SVM analysis, we select a linear SVM with a training set size of 45 (see Appendix S1, Sections E, F & G).

For both our SVM predictions and logistic regressions, we determine the coefficients or feature weights associated with each variable. The feature weights for the linear SVM derive from the hyperplane; the absolute magnitude of the feature weight indicates a variable's relative importance compared to others resulting from the separation of the two classes. Feature weights are similar in their relative magnitude to variable coefficients estimated by logistic regression (that are shown in Appendix S1, Table E.1). To classify patients into the lowest patient activation group vs. the higher activation group for each boundary, we define a patient's score as the relative distance between their score and each of the three of the classification boundaries. To determine the feature weights' values, we run each test for the three classification boundaries for each training set size for 25 iterations and calculate an average value for these 25 iterations. For each iteration, a new, randomly sampled training set of size n was created and used, with the test data being the remaining data of size, $N–n$, as the training set data is removed.

Inferences: From this exploration, we were able to make three sets of preliminary inferences regarding the prediction results shown in Table 3. First, we find that it is possible to predict PAM levels using TECC. This is useful because patients in different activation levels need different support (Dixon et al. 2009, Rathert et al. 2012, Shively et al. 2013); this prediction helps providers better understand how to support their patients. Second, the predictive power of TECC

Table 3 SVM Feature Weights

	Level 1 vs. 2, 3, 4 (lowest activation boundary)	Levels 1, 2 vs. 3, 4 (middle activation boundary)	Levels 1, 2, 3 vs. 4 (highest activation boundary)
TECC	0.028	0.590	0.097
Older adult	0.040	0.061	0.031
Public/urban hospital	0.001	0.102	0.090
Low socioeconomic status	0.020	0.256	0.089

Note: SVM, support vector machine; TECC, technology enabled continuity of care.

has a much larger magnitude of feature weight at the middle separation (Level 1 and 2 vs. Level 3 and 4 separation is weighted at 0.59), when compared to other levels that are at 0.028 and 0.097, respectively. This can be translated to mean that TECC discriminates well between the lower and upper half of the activation scale. Because of the importance of understanding patient activation level, this gives us a good tool to predict those patients in the upper half of the activation scale. Third, we find that that Older Adult status is a stronger predictor of lower activation scores than the type of hospital the patient attended because of the relative magnitudes of the feature weights (0.040 compared to 0.001). However, for higher activation scores we cannot make the same inferences, as there is no single feature that dominate the prediction of patient activation score.

6.3. Theory Implications

Patients managing their own condition through self-care tasks such as consistently taking their prescribed medications, following a low salt diet, reaching a healthy weight and exercising regularly is a desirable goal (Artinian et al. 2002, Cameron et al. 2009). Although these tasks may seem straightforward, choosing these actions consistently is notoriously difficult (Dickson et al. 2013, Wolever and Dreusicke 2016). In the COPD and CHF contexts, our study advances the underlying theory by positing and testing a learning framework on the nuanced relation between PAM, TECC interventions and readmission as shown by our moderated mediation findings. And, the exploratory predictions show that the weight of TECC in determining PAM with middle level of PAM, and with the Older adult variable, are sizably larger than the rest of the predictors.

These findings offer opportunities for developing follow on studies. For instance, we note that the interpretations of prediction weights are receiving attention in terms of fairness and gaming issue, based on predictions driven by demographic factors, in the machine learning literature studies (Datta et al. 2017). Follow on work in patient activation ought to examine fairness issues when PAM predictions are used in medical decision-making. In parallel, there is growing interest in using personalized technology to provide interventions specific to a patient's context to support healthier behaviors (Hu et al. 2018). Thus, it ought to be possible to introduce additional constructs that refine predictions of patient activation. Allied possibility of gaming (between the health care providers and the patient), and potential for fairness in handling patients are issues that we identify as avenues for follow on research.

From an empirical standpoint, our results could be further explored by altering our study. Specifically, if a future study measured both intervention and control patients' PAM before discharge from a hospital, and after 30 days of TECC or no TECC, researchers could assess causality of effects. Additionally, future researchers could include immediacy of patients' health issues to extricate out the effects of PAM, sickness level, and readmissions to better support and explain our counterintuitive results of PAM's positive association with readmissions.

As another example, a potential future study could investigate medical adherence in the HIV population while augmenting the patient care input variables, with additional constructs, such as capacity of patient care facilities (McCoy and Johnson 2014). In such a study, patient-related variables could be extended with behavioral constructs, such as such as willingness to change and forgetfulness (Chesney et al. 2000). It might also be possible to inform the design of the controlled study in real time with better estimates of demand based on outcomes of machine learning analysis (see Bertsimas et al. 2016, for a discussion of related ideas). These are potentially useful ways to extend and to implement our framework.

6.4. TECC Process Improvement

We note that the health care providers in the TECC intervention received daily updates from their patients through the equipment. These updates included objective readings (e.g., blood pressure, weight, etc.) and perceptive measures (e.g., extent to which patient felt tired or short of breath, etc.). However, due to the pre-specified nature of the experimental design (i.e., IRB approval mentioned in Appendix S1, Section A), we did not track such fine-grained data, but suggest such data could better support our learning framework. We therefore deem this to be a proof-of-concept study for our theory framework and restrict our claims to this study as additional theoretical analysis and field studies are needed before the proposed framework can be generalizable. For instance, the health care providers concentrated teleconferences in the start of the month-long continuity of care process (three contacts in week 1, two in week 2 and one in week 3). Health care operations models have examined dual causality between patient medical adherence and optimal resource allocation (McCoy and Johnson 2014). In such a setting, asking what is the most effective schedule (e.g., front- vs. back-loaded) and its impact on allocation resources based on perceived distribution of activation raises a useful theoretical question. We also note that the model does not account for the degradation of patient condition in the period of observation as has been shown in the literature (Bavafa et al. 2018, Deo et al. 2013). We justify this shortfall based on the readmission rates in the control population are relatively low (10.5%). A longer time horizon may lead to higher readmission rates and call for explicit modeling of the patient's deterioration during the period of observation. Scheduling of health care providers and patient deterioration provide future research opportunities.

6.5. Limitations

This study has several limitations. Some variables were observed but not measured (because they were not in the IRB-approved design), and thus were not incorporated into the learning prediction model. For instance, patients reported their vital conditions daily, which were observed by the health care providers but not incorporated into the dataset. Similarly, some patients visited their health care providers during the 30-day observation period, but this data was not collected. Also, the learning framework alludes to observed, but not measured constructs (e.g., self-care decisions and exact schedules for the nursing care provided), which could be documented to provide a firmer baseline for further analysis. Additionally, we collected patient activation data *after* TECC use; future researchers may want to collect this data pre and post intervention. This data suffers from attrition bias in that the intervention group had a much higher response rate (93.2%) vs. the control group (51.6%). Although a higher response rate from the control group would have been preferred, the combination of higher PAM scores, coupled with readmission rates provides complementary data supporting the efficacy of the intervention. Finally, patients are very complex. Because of this complexity, readmissions are typically driven by multiple factors, beyond TECC and PAM. Future researchers may want to further investigate the TECC—PAM—Readmissions relationship, taking into consideration the limitations of this research and further investigating the complex relationship of health condition progression with desires to manage one's condition, and odds of hospital readmissions.

7. Conclusions

To assess the relationships among TECC, patient activation and readmissions, we developed an error correction framework and tested four related hypotheses. Using this framework, we establish a relationship between TECC and an increase in patient activation levels. Our data show that when TECC acts through PAM, the net effect (shown in Figure 3) is that a combination of PAM and TECC reduces readmission for all values of PAM. And, as PAM rises, the percentage impact of TECC on the base case readmissions (i.e., no TECC) improves. That is, this work shows that a remote intervention is associated with higher PAM and fewer readmissions, thus extending the existing literature (e.g., Shane-McWhorter et al. 2015). We conclude by identifying a series of follow-up studies that could hasten the implementation of the proposed technology to simultaneously improve patient outcomes and health care operations needed for enhancing patient activation.

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References

Alegría, M., W. Sribney, D. Perez, M. Laderman, K. Keefe. 2009. The role of patient activation on patient–provider communication and quality of care for US and foreign born Latino patients. *J. Gen. Intern. Med.* **24**(3): 534–541.

Anderson, E. G. Jr., K. Lewis. 2014. A dynamic model of individual and collective learning amid disruption. *Organ. Sci.* **25**(2): 356–376.

Anderson, D., B. Golden, E. Wasil, H. Zhang. 2015. Predicting prostate cancer risk using magnetic resonance imaging data. *IseB* **13**(4): 599–608.

Argyris, C. 1976. Single-loop and double-loop models in research on decision making. *Adm. Sci. Q.* **21**(3): 363–375.

Argyris, C., D. A. Schon. 1974. *Theory in Practice: Increasing Professional Effectiveness*. Jossey-Bass, San Francisco, CA.

Artinian, N. T., M. Magnan, M. Sloan, M. P. Lange. 2002. Self-care behaviors among patients with heart failure. *Heart Lung: J. Acute Crit. Care* **31**(3): 161–172.

Aung, E., M. Donald, G. M. Williams, J. R. Coll, S. A. Doi. 2015. Joint influence of patient-assessed chronic illness care and patient activation on glycaemic control in type 2 diabetes. *Int. J. Qual. Health Care* **27**(2): 117–124.

Bavafa, H., L. M. Hitt, C. Terwiesch. 2018. The impact of e-visits on visit frequencies and patient health: Evidence from primary care. *Management Science* **64**(12): 5461–5480.

Begum, N., M. Donald, I. Z. Ozolins, J. Dower. 2011. Hospital admissions, emergency department utilisation and patient activation for self-management among people with diabetes. *Diabetes Res. Clin. Pract.* **93**(2): 260–267.

Bentley, B., M. J. De Jong, D. K. Moser, A. R. Peden. 2005. Factors related to nonadherence to low sodium diet recommendations in heart failure patients. *Eur. J. Cardiovasc. Nurs.* **4**(4): 331–336.

Bertsimas, D., A. O'Hair, S. Relyea, J. Silberholz. 2016. An analytics approach to designing clinical trials for cancer. *Management Sci.* **62**(5): 1511–1531.

Bodenheimer, T., K. Lorig, H. Holman, K. Grumbach. 2002. Patient self-management of chronic disease in primary care. *JAMA* **288**(19): 2469–2475.

Bourbeau, J., M. Julien, F. Maltais, M. Rouleau, A. Beaupré, R. Bégin, P. Renzi, D. Nault, E. Borycki, K. Schwartzman, R. Singh, J. Collet. 2003. Reduction of hospital utilization in patients with chronic obstructive pulmonary disease: A disease-specific self-management intervention. *Arch. Intern. Med.* **163**(5): 585–591.

Cameron, J., L. Worrall-Carter, B. Riegel, S. K. Lo, S. Stewart. 2009. Testing a model of patient characteristics, psychologic status, and cognitive function as predictors of self-care in persons with chronic heart failure. *Heart Lung: J. Acute Crit. Care* **38**(5): 410–418.

Carman, K. L., P. Dardess, M. Maurer, S. Sofaer, K. Adams, C. Bechtel, J. Sweeney. 2013. Patient and family engagement: A framework for understanding the elements and developing interventions and policies. *Health Aff.* **32**(2): 223–231.

Charlson, M. E., P. Pompei, K. L. Ales, C. R. MacKenzie. 1987. A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation. *J. Chronic Dis.* **40** (5): 373–383.

Chase, D. 2012. Patient engagement is the blockbuster drug of the century. *Forbes*, September 9.

Cheng, S., C. Chen, Y. Hou. 2010. A longitudinal examination of continuity of care and avoidable hospitalization: Evidence from a universal coverage health care system. *Arch. Intern. Med.* **170**(18): 1671–1677.

Chesney, M. A., M. Morin, L. Sherr. 2000. Adherence to HIV combination therapy. *Soc. Sci. Med.* **50**(11): 1599–1605.

Cole, C., G. Laurent, A. Drolet, J. Ebert, A. Gutchess, R. Lambert-Pandraud, E. Mullet, M. I. Norton, E. Peters. 2008. Decision making and brand choice by older consumers. *Market. Lett.* **19** (3–4): 355–365.

Cortes, C., V. Vapnik. 1995. Support-vector networks. *Mach. Learn* **20**(3): 273–297.

Coulter, A., S. Parsons, J. Askham. 2008. *Where are the Patients in Decision-Making about Their Own Care?* World Health Organization Regional Office for Europe, Copenhagen.

Datta, A., M. Fredrikson, G. Ko, P. Mardziel, S. Sen. 2017. Proxy non-discrimination in data-driven systems. arXiv preprint arXiv:1707.08120.

Deo, S., S. Iravani, T. Jiang, K. Smilowitz, S. Samuelson. 2013. Improving health outcomes through better capacity allocation in a community-based chronic care model. *Oper. Res.* **61**(6): 1277–1294.

Dickson, V. V., B. Riegel. 2009. Are we teaching what patients need to know? Building skills in heart failure self-care. *Heart Lung: J. Acute Crit. Care* **38**(3): 253–261.

Dickson, V. V., M. M. McCarthy, A. Howe, J. Schipper, S. M. Katz. 2013. Sociocultural influences on heart failure self-care among an ethnic minority black population. *J. Cardiovasc. Nurs.* **28**(2): 111–118.

Dixon, A., J. H. Hibbard, M. Tusler. 2009. How do people with different levels of activation self-manage their chronic conditions? *Patient: Patient-Centered Outcomes Res.* **2**(4): 257–268.

Fowles, J. B., P. Terry, M. Xi, J. H. Hibbard, C. T. Bloom, L. Harvey. 2009. Measuring self-management of patients' and employees' health: Further validation of the patient activation measure (PAM) based on its relation to employee characteristics. *Patient Educ. Couns.* **77**(1): 116–122.

Fries, J. F., S. T. Fries, C. L. Parcell, H. Harrington. 1992. Health risk changes with a low-cost individualized health promotion program: Effects at up to 30 months. *Am. J. Health Promot.* **6** (5): 364–371.

Gawande, A. 2011. Personal best. *The New Yorker*, October 3, pp. 44–53.

Gerteis, J., D. Izrael, D. Deitz, L. LeRoy, R. Ricciardi, T. Miller, J. Basu. 2014. *Multiple Chronic Conditions Chartbook*. AHRQ Publications No Q14–0038. Agency for Healthcare Research and Quality, Rockville, MD.

Gourevitch, M. N., D. Malaspina, M. Weitzman, L. R. Goldfrank. 2008. The public hospital in American medical education. *J. Urban Health* **85**(5): 779–786.

Graffigna, G., S. Barello, A. Bonanomi. 2017. The role of Patient Health Engagement Model (PHE-model) in affecting patient activation and medication adherence: A structural equation model. *PLoS ONE* **12**(6): e0179865.

Grandes, G., A. Sánchez, J. Torcal, R. O. Sánchez-Pinilla, K. Lizarraga, J. Serra. 2008. Targeting physical activity promotion in general practice: Characteristics of inactive patients and willingness to change. *BMC Public Health* **8**(1): 172.

Greene, J., J. H. Hibbard. 2012. Why does patient activation matter? An examination of the relationships between patient activation and health-related outcomes. *J. Gen. Intern. Med.* **27**(5): 520–526.

Greene, J., J. H. Hibbard, R. Sacks, V. Overton, C. D. Parrotta. 2015. When patient activation levels change, health outcomes and costs change, too. *Health Aff.* **34**(3): 431–437.

Guthrie, B., J. W. Saultz, G. K. Freeman, J. L. Haggerty. 2008. Continuity of care matters. *BMJ* **337**: a867.

Haggerty, J. L., R. J. Reid, G. K. Freeman, B. H. Starfield, C. E. Adair, R. McKendry. 2003. Continuity of care: A multidisciplinary review. *BMJ* **327**(7425): 1219–1221.

Harvey, L., J. B. Fowles, M. Xi, P. Terry. 2012. When activation changes, what else changes? The relationship between change in patient activation measure (PAM) and employees' health status and health behaviors. *Patient Educ. Cuns.* **88**(2): 338–343.

Hayes, A. F. 2013. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. The Guilford Press, New York.

Helm, J. E., A. Alaeddini, J. M. Stauffer, K. M. Bretthauer, T. A. Skolarus. 2015. Reducing hospital readmissions by integrating empirical prediction with resource optimization. *Prod. Oper. Manag.* **25**(2): 233–257.

Hendriks, M., J. Rademakers. 2014. Relationships between patient activation, disease-specific knowledge and health outcomes among people with diabetes; a survey study. *BMC Health Serv. Res.* **14**(1): 393.

Hibbard, J. H., J. Greene. 2013. What the evidence shows about patient activation: Better health outcomes and care experiences; fewer data on costs. *Health Aff.* **32**(2): 207–214.

Hibbard, J. H., E. R. Mahoney, J. Stockard, M. Tusler. 2005. Development and testing of a short form of the patient activation measure. *Health Serv. Res.* **40**(6p1): 1918–1930.

Hibbard, J. H., J. Greene, M. Tusler. 2009. Improving the outcomes of disease-management by tailoring care to the patient's level of activation. *Am. J. Manag. Care* **15**(6): 353–360.

Hibbard, J. H., J. Greene, Y. Shi, J. Mittler, D. Scanlon. 2015. When patient activation levels change, health outcomes and costs change, too. *Health Aff.* **34**(3): 430–437.

Holman, H., K. Lorig. 2004. Patient self-management: A key to effectiveness and efficiency in care of chronic disease. *Public Health Rep.* **119**(3): 239.

Please Cite this article in press as: Queenan, C., et al. Patient Heal Thyself: Reducing Hospital Readmissions with Technology-Enabled Continuity of Care and Patient Activation. *Production and Operations Management* (2019), https://doi.org/10.1111/poms.13080

Hu, X., P.-Y. S. Hsueh, C.-H. Chen, K. M. Diaz, F. E. Parsons, I. Ensari, M. Qian, Y.-K. K. Cheung. 2018. An interpretable health behavioral intervention policy for mobile device users. *IBM J. Res. Dev.* **62**(1): 4. https://doi.org/10.1147/JRD.2017.2769320

Jencks, S. F., M. V. Williams, E. A. Coleman. 2009. Rehospitalizations among patients in the Medicare fee-for-service program. *N. Engl. J. Med.* **360**(14): 1418–1428.

Leigh, J. P., N. Richardson, R. Beck, C. Kerr, H. Harrington, C. L. Parcell, J. F. Fries. 1992. Randomized controlled study of a retiree health promotion program: The Bank of America study. *Arch. Intern. Med.* **152**(6): 1201–1206.

Marshall, R., M. C. Beach, S. Saha, T. Mori, M. O. Loveless, J. H. Hibbard, J. A. Cohn, V. L. Sharp, P. T. Korthuis. 2013. Patient activation and improved outcomes in HIV-infected patients. *J. Gen. Intern. Med.* **28**(5): 668–674.

McCoy, J. H., M. E. Johnson. 2014. Clinic capacity management: Planning treatment programs that incorporate adherence. *Prod. Oper. Manag.* **23**(1): 1–18.

Mitchell, S. E., P. M. Gardiner, E. Sadikova, J. M. Martin, B. W. Jack, J. H. Hibbard, M. K. Paasche-Orlow. 2014. Patient activation and 30-day post-discharge hospital utilization. *J. Gen. Intern. Med.* **29**(2): 349–355.

Olsen, J. M., B. J. Nesbitt. 2010. Health coaching to improve healthy lifestyle behaviors: An integrative review. *Am. J. Health Promot.* **25**(1): e1–e12.

Parry, C., H. M. Kramer, E. A. Coleman. 2006. A qualitative exploration of a patient-centered coaching intervention to improve care transitions in chronically ill older adults. *Home Health Care Serv. Q* **25**(3–4): 39–53.

Patient Protection and Affordable Care Act (PPACA). 2010. Pub. L. No. 111-148, §2702, 124 Stat. 119, 318–319.

Rask, K. J., M. V. Williams, R. M. Parker, S. E. McNagny. 1994. Obstacles predicting lack of a regular provider and delays in seeking care for patients at an urban public hospital. *JAMA* **271**(24): 1931–1933.

Rathert, C., M. D. Wyrwich, S. A. Boren. 2012. Patient-centered care and outcomes: A systematic review of the literature. *Med. Care Res. Rev.* **70**(4): 351–379.

Regenstein, M., J. Huang, L. Cummings, D. Lessler, B. Reilly, D. Schillinger. 2005. Caring for patients with diabetes in safety net hospitals and health systems. The Commonwealth Fund, publication number 826.

Riegel, B., V. V. Dickson, L. R. Goldberg, J. A. Deatrick. 2007. Factors associated with the development of expertise in heart failure self-care. *Nurs. Res.* **56**(4): 235–243.

Rockwell, J. M., B. Riegel. 2001. Predictors of self-care in persons with heart failure. *Heart Lung* **30**(1): 18–25.

Rosenstock, I. M., V. J. Strecher, M. H. Becker. 1988. Social learning theory and the health belief model. *Health Educ. Behav.* **15**(2): 175–183.

Senot, C. 2019. Continuity of care and risk of readmission: An investigation into the healthcare journey of heart failure patients. *Prod. Oper. Manag.* https://doi.org/10.1111/poms.13027

Senot, C., A. Chandrasekaran, P. T. Ward, A. L. Tucker, S. D. Moffatt-Bruce. 2016. The impact of combining conformance and experiential quality on hospitals' readmissions and cost performance. *Management Sci.* **62**(3): 829–848.

Shane-McWhorter, L., C. McAdam-Marx, L. Lenert, M. Petersen, S. Woolsey, J. M. Coursey, T. C. Whittaker, C. Hyer, D. LaMarche, P. Carroll, L. Chuy. 2015. Pharmacist-provided diabetes management and education via a telemonitoring program. *J. Am. Pharm. Assoc.* **55**(5): 516–526.

Shively, M. J., N. J. Gardetto, M. F. Kodiath, A. Kelly, T. L. Smith, C. Stepnowsky, C. Maynard, C. B. Larson. 2013. Effect of patient activation on self-management in patients with heart failure. *J. Cardiovasc. Nurs.* **28**(1): 20–34.

Street, R. L., G. Makoul, N. K. Arora, R. M. Epstein. 2009. How does communication heal? Pathways linking clinician–patient communication to health outcomes. *Patient Educ. Couns.* **74**(3): 295–301.

Tsai, A. C., S. C. Morton, C. M. Mangione, E. B. Keeler. 2005. A meta-analysis of interventions to improve care for chronic illnesses. *Am. J. Manag. Care* **11**(8): 478–488.

Tucker, A. L., A. C. Edmondson. 2003. Why hospitals don't learn from failures: Organizational and psychological dynamics that inhibit system change. *Calif. Manage. Rev.* **45**(2): 55–72.

Turner, A., J. K. Anderson, L. M. Wallace, C. Bourne. 2015. An evaluation of a self-management program for patients with long-term conditions. *Patient Educ. Couns.* **98**(2): 213–219.

Van Servellen, G., M. Fongwa, E. Mockus D'Errico. 2006. Continuity of care and quality care outcomes for people experiencing chronic conditions: A literature review. *Nurs. Health Sci.* **8**(3): 185–195.

Van Walraven, C., N. Oake, A. Jennings, A. J. Forster. 2010. The association between continuity of care and outcomes: A systematic and critical review. *J. Eval. Clin. Pract.* **16**(5): 947–956.

Wagner, E. H., B. T. Austin, M. Korff. 1996. Organizing care for patients with chronic illness. *Milbank Q.* **74**(4): 511–544.

Wagner, E. H., B. T. Austin, C. Davis, M. Hindmarsh, J. Schaefer, A. Bonomi. 2001. Improving chronic illness care: Translating evidence into action. *Health Aff.* **20**(6): 64–78.

Warwick, M., R. Gallagher, L. Chenoweth, J. Stein-Parbury. 2010. Self-management and symptom monitoring among older adults with chronic obstructive pulmonary disease. *J. Adv. Nurs.* **66**(4): 784–793.

Wiedemann, A. U., B. Schüz, F. Sniehotta, U. Scholz, R. Schwarzer. 2009. Disentangling the relation between intentions, planning, and behaviour: A moderated mediation analysis. *Psychol. Health* **24**(1): 67–79.

Wolever, R. Q., M. H. Dreusicke. 2016. Integrative health coaching: A behavior skills approach that improves HbA1c and pharmacy claims-derived medication adherence. *BMJ Open Diabetes Res. Care* **4**(1): e000201.

Zimbudzi, E., C. Lo, S. Ranasinha, P. G. Kerr, K. R. Polkinghorne, H. Teede, T. Usherwood, R. G. Walker, G. Jonhson, G. Fulcher, S. Zoungas. 2017. The association between patient activation and self-care practices: A cross-sectional study of an Australian population with comorbid diabetes and chronic kidney disease. *Health Expect.* **20**(6): 1375–1384.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1:

Section A: Design, Timeline and PAM Questions
Section B: Technology Implementation
Section C: Continuity of Care Procedures
Section D: Comparison between Properties of Logistic Regression and Linear Support Vector Machines
Section E: Logistic Regression
Section F: Comparison between Linear, Gaussian, and Polynomial Support Vector Machines
Section G: Cross Validation Loss for SVM Estimator.