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CASCADING FEEDBACK: A LONGITUDINAL STUDY OF A FEEDBACK ECOSYSTEM FOR TELEMONITORING PATIENTS WITH CHRONIC DISEASE[1]

Kathryn Brohman, Shamel Addas, and Jeff Dixon
Smith School of Business, Queen's University, Kingston, Ontario CANADA K7L 3N6
{kathryn.brohman@queensu.ca} {shamel.addas@queensu.ca} {6jad3@queensu.ca}

Alain Pinsonneault
Desautels Faculty of Management, McGill University, 1001 Sherbrooke Street West,
Montréal, Quebec CANADA H3A 1G5 {alain.pinsonneault@mcgill.ca}

While telemonitoring technology is widely used in treatment of patients with chronic diseases, our understanding of how it influences patient-related outcomes is limited. Drawing upon feedback intervention theory, the paper develops a model that examines how a telemonitoring feedback ecosystem (patient, telemonitoring technology, care provider) is related to patient behavioral outcomes. More precisely, we study the cascading effects of two types of technology feedback (medical and compliance alerts) on the provision of three types of feedback (outcome, corrective, and personal) given by care providers, and how the feedback in turn is related to patient adaptation and ultimately to calls to 911. Using generalized linear mixed modeling, we tested our hypotheses with longitudinal data from 212 patients with chronic obstructive pulmonary disease (COPD) and/or chronic heart failure (CHF) over 26 weeks. Our results show that medical alerts had a positive association with all three types of provider feedback. By contrast, compliance alerts had curvilinear relationships with corrective and personal feedback. Our results also show that outcome feedback and personal feedback were associated with increases in patient adaptations. Patient adaptation was negatively related to the odds of calling 911. Interestingly, we found a significant negative interaction between outcome and corrective feedback and patient adaptation. Finally, our results show that while the frequency of feedback decreased over the life of the program, the amount of adaptations increased over the same period, which suggests that patient self-management improved over time. By examining a telemonitoring-based ecosystem with two stages of feedback, our study contributes to the chronic disease management literature as well as to other contexts where monitoring technologies deliver feedback that is mediated by a third party. Theoretical and practical implications of our study are discussed.

Keywords: Telemonitoring, health information technology, patient adaptation, feedback intervention theory, feedback ecosystem, multilevel modeling, generalized linear mixed models

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Introduction and Motivation

Chronic diseases—such as chronic heart failure (CHF), chronic obstructive pulmonary disease (COPD), and diabetes—refer to illnesses that last at least three months, have no known cure, and require medical attention (Rijken and Dekker 1998). Chronic illnesses affect more than half of the American adult population and are responsible for 86% of all healthcare spending (Kvedar et al. 2016) and 60% of deaths worldwide (Solis 2016). With the rapid increase in the number of senior citizens, the problems related to chronic disease management are likely to intensify.

Because dealing with chronic conditions only at acute states in an episodic manner creates inefficiencies and burdens healthcare delivery systems (Gianchandani 2011), numerous efforts are being made to help patients self-manage their conditions on a continuous and preventive basis. One promising approach is the use of telemonitoring, defined as an automated process that employs information technology to help patients monitor their health conditions and transmit the corresponding health data from home to the appropriate health care setting (Paré et al. 2007). Telemonitoring technologies have recently been recognized for their potential to provide continuous feedback directly to patients and/or indirectly through interactions with their care providers (Kitsiou et al. 2015). Feedback from telemonitoring can enable early diagnosis, reductions in system burden, and more effective and efficient chronic disease management (Gianchandani 2011; Kalankesh et al. 2016; Peters et al. 2015).

To understand the potential benefits from the feedback provided by telemonitoring systems, the extant literature mostly adopts a techno-centric view that focuses on the direct links between telemonitoring technology and patient outcomes (e.g., Duan et al. 2017; Inglis 2010; Sahakyan et al. 2018; Seto et al. 2012). While these studies have advanced our understanding concerning some of the clinical (Duan et al. 2017; Sahakyan et al. 2018), structural (Inglis 2010; Kalankesh et al. 2016; Kitsiou et al. 2015), and behavioral (Morlion et al. 2002; Seto et al. 2012) outcomes of telemonitoring, they shed little light on the nature of the interactions and feedback that take place between care providers and patients, which could be responsible for those outcomes. For example, when patients receive feedback directly from their health tracking devices, the sheer amount of data may overwhelm them (Choe et al. 2014), and they may not have the expertise necessary to interpret the data (Mercer et al. 2016) or to capture the relevant triggers or context (Choe et al. 2014). Therefore, there may be value from having the feedback mediated through interactions with a care provider. However, extant studies have not fully captured the nuances of such interactions, focusing instead on crude measures such as the frequency of communication between providers and patients (e.g., Gómez et al. 2002; Mullan et al. 2003). In short, we argue that there is a need to understand how different technology triggers or alerts (technology feedback) and different attributes of feedback (provider feedback) affect patient outcomes.

In the telemonitoring literature, there is a call for an integrative approach that encompasses the technology and the mechanisms through which providers coordinate and deliver care to patients (Kitsiou et al. 2015). Similarly, in IS research, it has long been suggested that the effects of a technology result from technology–people interactions around its use (e.g., Beaudry and Pinsonneault 2005; Orli-kowski and Scott 2008).

The present paper addresses these issues. Drawing upon feedback intervention theory (Kluger and DeNisi 1996), we examine the impact of a feedback ecosystem (technology–provider–patient interactions) on patient behavioral outcomes. This ecosystem is an environment that connects technology, patients, and care providers (in our case community paramedics, or CPs) through regular and timely feedback. Technology delivers feedback (alerts) to providers on patients' health results in the first stage and providers give feedback to patients in the second stage (herein provider feedback or CP feedback). We used a comprehensive data set that combines secondary data and content analysis data coded from the providers' qualitative notes. Our research design provides rigor in both the assessment of patient behavioral outcomes (which are assessed by the providers, rather than being self-reported by patients) and in capturing the longitudinal effects of telemonitoring on 212 chronically ill patients observed over 26 weeks.

The paper makes three research contributions through the introduction of a cascading feedback framework comprising two stages of feeddback. First, the framework offers a rich account of how the effects of telemonitoring cascade from technology to patient and are mediated by feedback from care providers. We show that different types of feedback at each stage have different effects on provider actions and on patient adaptation. Our study thus provides a nuanced understanding of how dif-ferent dimensions of feedback benefit chronically ill patients. We treat feedback not as a unitary concept, but rather dis-aggregate it into two distinct types of technology feedback (medical and compliance alerts) and three types of provider feedback (outcome, corrective, and personal). We hypothe-size and test the differential effects of these feedback types.

Second, our cascading feedback framework contributes back to feedback intervention theory. The theory recognizes that feedback givers can participate in the process of self-regulating the behaviors of feedback receivers (e.g., through goal setting and feedback provision). Our work goes one step further by recognizing that self-regulation can be socially mediated (Volet et al. 2009). That is, feedback givers also regulate their own behaviors around the goals of feedback receivers and use technology as a source of feedback that they then filter, customize, and relay to the receivers in a way receivers can understand and use. This idea that feedback can cascade through a two-stage feedback ecosystem satisfies a key premise of the theory, which specifies that to draw attention, feedback must not tax cognitive resources and receivers must be capable of interpreting it meaningfully (Kluger and DeNisi 1996). Our contribution regarding the cascading effect of feedback can extend beyond the healthcare context to other settings where monitoring technologies deliver feedback that is mediated by a third party (e.g., targeted university advising systems; suicide alert systems on social media).

Finally, by focusing on behavioral outcomes that are proximal in nature, namely patient adaptation and calls to 911, the present study addresses some of the limitations of using distal outcome measures, such as clinical (e.g., blood pressure) and structural (e.g., hospitalization) outcomes. In particular, our proximal measures are directly under the control of the patients, whereas clinical and structural outcomes can be affected by many factors that go beyond what patients do with technology or what feedback is given to them (e.g., medication use, environmental or social factors, personal events). Moreover, these proximal measures are well aligned with the goals of telemonitoring programs of empowering patients to manage their own care in the comfort of their homes while reducing the burden on the healthcare delivery system.

Theoretical and Contextual Boundaries

We conceptualize a telemonitoring-based feedback ecosystem as comprising telemonitoring technologies (monitoring devices connected to a central system), a care provider, and a patient (see Figure 1). Patients take readings of their vital signs at home using the devices, which send the data automatically to the care provider's central system. The first function of the feedback ecosystem is to alert providers that a discrepancy has occurred (first feedback stage). Alerts are generated automatically by the central system. Our investigation covers two types of alerts afforded by telemonitoring technology and previously identified as important, namely medical and compliance alerts (Sahakyan et al. 2018; Seto et al. 2012). Medical alerts indicate a health-related discrepancy and are triggered when one or more of a patient's vital signs are outside the normal threshold prescribed by the patient's physician. Compliance alerts indicate a discrepancy related to a patient's use of the technology (i.e., neglecting to take vital signs readings). Both types of alerts deliver feedback to providers, who may respond depending on how the alert is interpreted. When providers act on the alerts, they initiate interactions with patients—through text messaging, phone calls, or home visits—in which they give feedback aimed at getting patients to adapt their behaviors (second feedback stage). Our theoretical development examines the effects of specific attributes of technology-based and provider-based feedback on patient adaptation in the context of telemonitoring and chronic disease.

The providers giving feedback to patients have traditionally been nurses, primary care physicians, and specialists (Kitsiou et al. 2015). However, an emerging trend is the use of community paramedics (CPs) as providers for chronically ill patients. In their expanded roles, CPs are trained to monitor and provide feedback to help patients manage their health conditions (Abrashkin et al. 2016). CPs are particularly relevant to home telemonitoring as they are a well-trained mobile workforce in the community (Bigham et al. 2013; Choi et al. 2016). In this research, we focus on the feedback provided by CPs to chronically ill patients enrolled in a program called Community Paramedic Remote Patient Monitoring (CPRPM).

Theoretical Development

We draw on feedback intervention theory (Kluger and DeNisi 1996) to better understand the role of the feedback ecosystem in the context of telemonitoring. Feedback intervention theory is concerned with how individuals regulate their goal-directed behaviors based on external feedback they receive from the environment. A feedback intervention is defined as "actions taken by (an) external agent(s) to provide information regarding some aspect(s) of one's task performance" (Kluger and DeNisi 1996, p. 255)[2]. The essence of the theory is that feedback enables individuals to be made aware of result-goal discrepancies and changes the locus of attention to affect behaviors in order to reduce those discrepancies. Depending on the situation and type of feedback involved, attention is directed to different levels of goal hierarchy, which has an impact on subsequent behavior adjustment and task performance (Kluger and DeNisi 1996). Feedback intervention theory draws on other self-regulation theories—especially control theory (Carver and Scheier 1982)—and on Ilgen et al.'s (1979) review of the feedback literature to develop five interrelated premises. Next, we present these

[2]In this paper, we use the terms *feedback intervention* and *feedback* interchangeably.

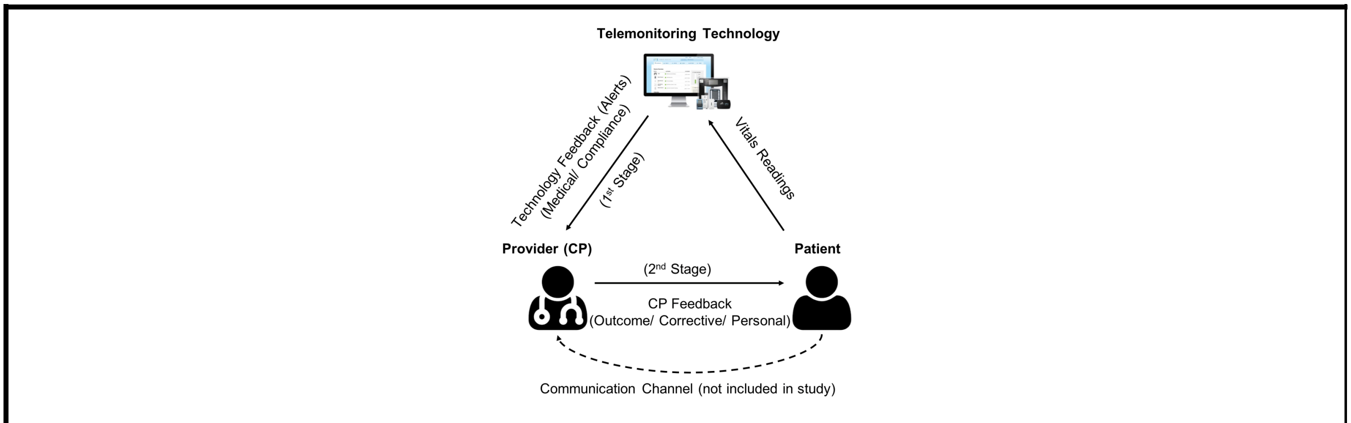

Figure 1. The Feedback Ecosystem

premises and describe how we leverage them to develop our theoretical model (see Appendix A for a summary). Our goal is not to formally test the premises, but to use the theory as a meta-framework to inform and guide our understanding of the cascading effect of the feedback ecosystem we studied.

The first premise of the theory suggests that behavior is regulated through feedback that enables individuals to control discrepancies between a present state (in our case, a patient's health result) and a goal that is set internally or externally (in our case, a physician sets clinical thresholds and a CP sets program goals). Our work extends the theory by holding that behavior regulation can be socially mediated (Lord et al. 2010; Volet et al. 2009). That is, both CPs and patients regulate their behaviors through feedback that cascades via two stages. In the first stage, technology feedback (medical and compliance alerts) is given to CPs to signal discrepancies in patients' health results, which triggers CP actions. In the second stage, CPs give feedback (outcome, corrective, and personal) to patients based on the discrepancies. The feedback helps patients to perform adaptations around managing their care (self-managing their condition and seeking help when needed).

According to the second premise, goals exist within hierarchically nested self-regulation systems. Feedback intervention theory focuses on three regulation levels. The upper level includes meta-task goals that are more abstract (in our case, patient quality of life and well-being) and that activate self-related processes. The intermediate level includes goals related to a present state (i.e., managing a patient's condition, such as breathing discomfort, through self-care or seeking help), which activates motivational processes. Finally, the lower level includes goals related to concrete actions for managing the task or state (e.g., administer supplemental oxygen). These goals activate learning processes (Kluger and DeNisi 1996). The output of higher-level processes set, change, or constrain the goals for the lower levels, and lower level-processes contribute to attaining the goals set for the higher levels (Rasmussen et al. 2006).

The third premise suggests that a discrepancy must receive attention to regulate behavior. This occurs when the discrepancy is salient and goal-relevant and when the corresponding feedback does not overburden cognitive resources (Kluger and DeNisi 1996). Ilgen et al. (1979) argued that information about a discrepancy becomes important when individuals are in a position to interpret it meaningfully and when the feedback offers an incremental increase in information about their behaviors over and above what they already know (i.e., high information value). In our case, discrepancies in patients' health outcomes that are perceived at any level of the hierarchy draw the attention of CPs (in the first stage) and their patients (in the second stage). Discrepancies draw attention because managing patient care is an important goal that is shared by providers and patients (Kitsiou et al. 2015). In the first stage, the medical and compliance alerts are received by medically trained CPs and draw their attention to particular patients and to discrepancies in those patients' vitals readings. While alerts are filtered and prioritized by severity, we will later argue that some alert types (compliance alerts) can overload the cognitive resources of CPs and that they provide relatively low information value. In the second stage, the CP feedback draws patients' attention to the discrepancies. The patients receive feedback that had already been filtered and prioritized by the CPs in the first stage and customized to their situation in the second stage. Hence, the feedback is communicated in a way that patients can understand and use without becoming overwhelmed with too much information.

According to the theory's fourth premise, attention is normally directed at a moderate (focal task) level of the hierarchy. The lower level of regulation (i.e., task detail) is often suppressed because individuals execute many tasks automatically by drawing on scripts and schemas (unless the task is new or complex, or feedback is received that directs attention to the level of task detail) (Kluger and DeNisi 1996). Similarly, the upper level of regulation (self-level) is often suppressed below activation to allow individuals to focus on managing their focal task or present state, without getting distracted by abstract, self-related goals (Lord et al. 2010).

The final premise delineates what level(s) in the hierarchy will receive attention from what types of feedback and the outcomes that follow. Feedback interventions can redirect attention upward or downward in the hierarchy. Feedback intervention theory stipulates differential effects of feedback depending on feedback and task attributes and the level at which feedback directs attention. This study examines three main types of feedback: (1) outcome feedback (information about the state of one's performance results), (2) corrective feedback (information about the process that led to the discrepancy and/or the means for reducing it), and (3) personal feedback (information that projects a sense of care, appears well-intentioned, is sensitive to the emotional and cognitive needs of the individual, and shows a pathway to improvement (see Fong et al. 2018)). We now describe these feedback types and how they relate to the theory's fifth premise.

According to the theory, outcome feedback can focus attention at the intermediate (focal task) level—the level at which attention is normally directed—and activate motivational processes. Negative outcome feedback motivates individuals to expend greater effort (i.e., work harder) by implementing action programs from prior experience. If the increased effort does not reduce the discrepancy, attention may shift to the upper (self) or lower (task detail) level, depending on the extent of one's confidence or expectancy. Outcome feedback is effective mostly when the behaviors involved are relatively simple or familiar (DeNisi and Kluger 2000; Kluger and DeNisi 1996). In addition, the motivational effect of feedback interventions tends to be reinforced when they are provided repeatedly over time (Kluger and DeNisi 1996). Our study distinguishes between three subtypes of outcome feedback: knowledge of result, change in result, and rate of change or velocity (Kluger and DeNisi 1996). The technology feedback in our model (medical and compliance alerts) given to CPs in the first stage are considered knowledge of result feedback, because they merely convey information about the patient's health results. The CP-based outcome feedback given to patients in the second stage represents feedback about their health results (knowledge of result) as well as how much a patient's results have changed from a previous reference point (i.e., change in result), or how fast the results have changed over a given period of time. (i.e., velocity). In our model, we refer to the technology feedback simply as medical and compliance alerts, and we refer to the CP-based outcome feedback as *outcome feedback* (see Appendix B for construct definitions and operationalizations).

Corrective feedback is a type of process feedback that typically operates at the lower (task detail) level. By focusing attention at the lower level, negative corrective feedback can activate learning processes. This occurs when the motivational processes described above fail to reduce the discrepancy, or when the feedback originates directly at the lower level. Corrective feedback contains cues that enable individuals to work smarter by generating and testing hypotheses to correct errors and to find ways to reduce the discrepancy (e.g., try this and see how you feel tomorrow). Hypotheses that are confirmed by the results of subsequent behaviors enhance learning. Unconfirmed hypotheses lead to generating new hypotheses or quitting. Corrective feedback is effective for new or complex tasks. It can be ineffective for simple tasks but only if the feedback is immediate and interferes with the task as it is being performed (Vallacher and Wegner 1987). Feedback also needs to be given in an informational rather than a controlling manner (Ilgen et al. 1979; Kluger and DeNisi 1996).

A third type of feedback—conceptualized here as personal feedback—can direct attention at the upper (self) level and activate meta-task goals and processes. The theory suggests that when feedback is self-enhancing (e.g., constructive criticism) (Bouskila-Yam and Kluger 2011) and nonthreatening, it motivates individuals to work hard but with some attention diverted to meta-task goals. Performance is thus improved for simple tasks requiring fewer resources and reduced for complex tasks (Kluger and DeNisi 1998). Further, feedback that fosters self-efficacy endorses opportunities for attaining self-related goals. Attention is thus redirected to the intermediate level, motivating individuals to invest more effort. We build on these insights by introducing the concept of personal feedback. Personal feedback demonstrates emphatic concern for the receiver (Young et al. 2017) and is intended to help receivers address the emotions and cognitions that often accompany negative feedback. The feedback provided often conveys a considerate and nonthreatening tone (Steelman et al. 2004). It also fosters confidence and hope toward meeting the goal (Fong et al. 2018). Showing a pathway to improvement is conceptually distinct from providing corrective feedback. While the former is more general and focuses on motivating individuals and catering to their sense of self, the latter is more specific and provides specific cues and instructions that focus attention on task learning. In short, personal feedback focuses on the receiver rather than on specific task details.

Our coverage of these three feedback types (outcome, corrective, and personal), while not exhaustive, captures the essence of how providers can deliver feedback that affects behavior (i.e., by showing patients their discrepant outcomes via outcome feedback, telling them what to do via corrective feedback, and addressing their emotional and cognitive needs via personal feedback).

In sum, an integrative understanding of the five premises of feedback intervention theory and the different feedback types enable us to identify and tie together the main elements of our model presented below. An important issue to address is the time scale at which feedback is provided (Zaheer et al. 1999). Feedback intervention theory is inherently dynamic, which suggests that feedback should influence behavior regulation and performance over time (DeNisi and Kluger 2000). Feedback interventions have been studied at the micro and macro levels. At the micro level, laboratory studies have examined the effects of a single or a limited number of interventions on a specific immediate outcome, such as task performance (e.g., Ang et al. 1993; Earley et al. 1990). At the macro level, some field studies have looked at the longer-term impact of feedback as assessed over multiple (mostly two) points in time, months or years apart (e.g., Seifert and Yukl 2010). Our efforts focus on an intermediate time scale that captures how the repeated delivery of feedback—in our case, over the course of a 26-week telemonitoring program—is related to patient adaptation. Our longitudinal perspective enables us to examine within-person associations between feedback and patient adaptation.

Model and Hypotheses

The research model is shown in Figure 2. The model is guided by feedback intervention theory, but also extends the theory in three ways. First, by looking at how feedback cascades from technology to patient via two stages and is mediated by CP actions; second, by proposing what types of feedback are relevant for each stage; and, third, by identifying the impact of these feedback types on patient adaptation and on calls to 911.

Technology Feedback and CP Feedback

We expect that medical alerts (i.e., alerts pertaining to discrepancies in vitals signs) and compliance alerts (i.e., alerts pertaining to lack of adherence to using the technology) will have different effects on CP feedback. Because both alert types represent outcome feedback (specifically, knowledge of result feedback), they have the potential to direct the CP's attention at the intermediate level and activate motivational processes (premise #5). Because of goal alignment, CPs are generally motivated to process alerts and initiate feedback with patients to reduce discrepancies in those patients' results. According to the patient-centered care literature, providers see it as their role and responsibility to monitor discrepancies in their patients' health (especially medical) outcomes and to discuss those issues with them (Riemer et al. 2005). However, we argue that motivational processes will be differently activated owing to the nature of the discrepancies signaled by the two types of alerts. Medical alerts signal an anomaly in a patient's health status. That is, they suggest a potential or actual clinical problem that warrants attention. Because they have high information value, medical alerts will therefore draw the attention of CPs to particular patients and to particular discrepancies in those patients' health results. CPs are expected and motivated to act upon the alerts by initiating feedback with the patients. As a form of outcome feedback, medical alerts are sufficient to motivate CP action, because the task of feedback provision is relatively simple and well-learned by the providers who receive specific training in addressing patient issues (see premise #5).

We argue that medical alerts will elicit three types of CP feedback, each operating at a different level of the regulation hierarchy. First, given the potential seriousness of medical alerts, CPs may not merely relay the alert information to patients, but also consult their medical notes to offer specific information on the patient's medical trajectory (e.g., benchmark measures of patients' past readings, discrepancies in those readings, and patients' progress relative to past results and interventions). Hence, CPs deliver outcome feedback that conveys information about the change in patients' health-related results and/or the rate of change (velocity). Second, CPs will offer information on what patients should do to manage their discrepant condition (corrective feedback). Etkind et al.'s (2015) review showed that routine outcome monitoring enabled providers to give better feedback that responded to patients identified needs. Third, CPs will offer personal feedback that demonstrates care and focuses on patients' needs (e.g., Song et al. 2014). Evidence from the routine outcome monitoring literature shows that monitoring feedback outcomes during the course of therapy prompted providers to communicate with patients and to offer personal feedback on patients' conditions (Carlier et al. 2012). It was also argued that such feedback is effective when provided repeatedly and concurrently with treatment (Kelley and Bickman 2009). We thus hypothesize:

H1: Medical alerts have a positive relationship with outcome feedback.

H2: Medical alerts have a positive relationship with corrective feedback.

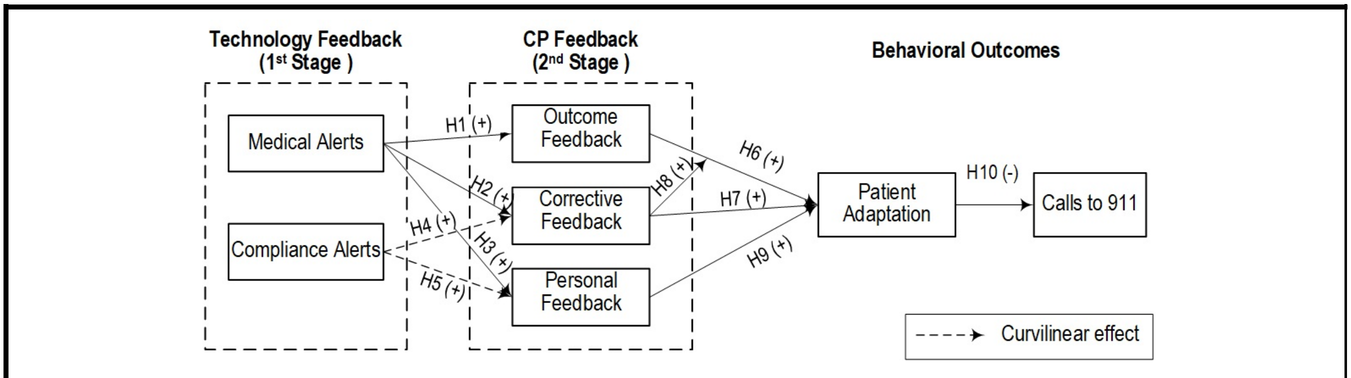

Figure 2. Research Model

H3: Medical alerts have a positive relationship with personal feedback.

Compliance alerts signal that a patient did not take his or her vitals readings. CPs are likely to respond by giving corrective feedback (e.g., ideas on how to improve compliance) and personal feedback (e.g., conveying a sense of care and that it is normal to sometimes miss a reading). However, two important points prevent compliance alerts from sustaining the attention of CPs (see premise #3). First, compliance alerts have a relatively low information value over time. Contrary to medical alerts, they do not signal an actual medical problem but rather a lapse in a patient's commitment to use the telemonitoring technology. The medical consequences of such lapses are often not as serious as for medical alerts. In addition, the marginal benefit of receiving repeated alerts regarding a patient who continues failing to comply is low. According to the theory, the usefulness of feedback depends on the incremental increase in information about the behavior over and above the information already available (Ilgen et al. 1979). As the number of compliance alerts increase, there is a higher chance that the information is already known to the provider (Tamblyn et al. 2008). CPs may deem it unnecessary to provide additional feedback beyond what has already been given. Stated simply, compliance alerts offer little new information over time and, therefore, their effect on motivating CP action can taper off over time.

Second, attention to compliance alerts is not sustained because CPs can become overwhelmed with the number of alerts to handle over and above their ongoing job functions. Alert fatigue has well-documented effects in the literature on computerized drug alerts. It is generally known that providers ignore or override alerts, especially when they face a large volume of alerts (Tamblyn et al. 2012). Several studies also describe a trend of declining providers' actions pertaining to allergy or drug alerts as the number of alerts increased, especially when the marginal increase in information provided by the alerts was low (Glassman et al. 2006; Tamblyn et al. 2008). Further, independent of whether or not the alerts are presented in an interruptive manner, the sheer volume of alerts interferes with providers' workflow (Tamblyn et al. 2008). Hence, alert fatigue is expected to accumulate with the number of received compliance alerts. To cope with alert fatigue, the CPs may become desensitized to the alerts as the volume of alerts increases and thus provide less feedback on aggregate. We therefore expect curvilinear relationships between compliance alerts and two types of CP feedback (corrective and personal).

We do not hypothesize a relationship between compliance alerts and outcome feedback because of the inherent mismatch between these two constructs. A compliance alert taps at the failure to take a reading whereas outcome feedback examines what one's reading is relative to prior readings (e.g., blood pressure is trending downward). We hypothesize the following:

H4: Compliance alerts have an inverted U-shaped relationship with corrective feedback.

H5: Compliance alerts have an inverted U-shaped relationship with personal feedback.

CP Feedback and Patient Adaptation

We expect that CP feedback will prompt patient adaptive behaviors (patients self-managing their care and seeking help when needed). Adaptation efforts include behavioral elements such as changes to the habits individuals develop and the tasks or procedures they implement, as well as cognitive elements such as changes to their beliefs and knowledge (i.e., learning) (Barki et al. 2007; Beaudry and Pinsonneault 2005).

Of note, many of the types of adaptation we examine are relatively quick to implement (e.g., going for a walk, breathing techniques, foot elevation, calling a clinic). Evidence from field settings shows that feedback is more effective with repeated exposure (Donia et al. 2018; Seifert and Yukl 2010; Smither et al. 2005). Some studies found that the effects of outcome feedback can taper off over time (Lam et al. 2011) or even hurt performance (Lurie and Swaminathan 2009). However, these studies focused on complex tasks and, as such, their findings were consistent with feedback intervention theory. Lam et al. (2011) argued that as long as the task is simple and the frequency of feedback does not overwhelm people's cognitive resources, higher feedback frequency is better.

Repeated feedback is especially important for chronically ill patients. In contrast to individuals receiving feedback for a specific, immediate task they perform, these patients require feedback that will help them manage their lifelong health conditions. Interventions for chronic disease patients often require a series of small steps that work progressively toward improving well-being (e.g., encouraging or discouraging certain behaviors, providing assurance, suggesting quick fixes). Repeated feedback provides more opportunities to draw patients' attention to health issues and to adjust adverse health-related behaviors and habits (Luoto and Carman 2014).

Importantly, in contrast to compliance alerts that occur in real time and for which we hypothesize curvilinear effects (H4, H5), the theoretical inflection point of the curve is unlikely to be reached with the volume of CP feedback given to patients with chronic disease. Because CPs filter the medical and compliance alerts and contact patients when they see a need, the amount of feedback ultimately delivered to the patients is unlikely to overwhelm them.

We now hypothesize the effects of the three types of feedback. The outcome feedback provided to patients includes information about the discrepancy, in addition to information about how the result compares to prior result(s). Outcome feedback directs patients' attention at the intermediate level of regulation and particularly on their health management goals. The motivational effect is especially strong when the feedback helps patients to understand how they deviated from prior results and thus to set specific goals and mobilize efforts to reduce the gap and progress toward their goals (Erez 1977; Kayande et al. 2009; Kluger and DeNisi 1996). For example, when patients are given feedback regarding their high blood pressure, how the result compares to previous results and to normal levels, and what the future health implications are (e.g., stroke), these patients will be motivated to invest more efforts (i.e., to work harder) to reduce the discrepancy. Such efforts constitute adaptations where patients take steps to either self-manage their condition or seek help. Outcome feedback thus enables individuals to gauge their rate of progress and to focus on aspects of their health that require improvement.

Research suggests that individuals who receive feedback about their outcomes (how they are doing relative to past results) can experience higher motivation and performance (Elicker 2010; Johnson et al. 2013), even when the velocity is negative (i.e., condition worsening at a faster rate than before) (Carver and Scheier 1990). Meta-analysis results suggest that outcome feedback helps direct attention to the task, provides a clear feedback standard discrepancy, and motivates people to work hard on reducing the discrepancy (Kluger and DeNisi 1996). A counterargument is that outcome feedback may decrease adaptation because, in cases where a negative discrepancy (in medical or compliance status) relative to previous results is communicated (i.e., negative change or velocity), individuals could become demotivated or reject the feedback (e.g., Ilgen et al. 1979). However, when the higher-level goal is important and people are committed to achieving it (in this case, patients being able to manage their chronic conditions), they treat outcome feedback as motivational and stay focused on achieving their immediate task goals (Carver and Scheier 1990). We hypothesize:

> *H6: Outcome feedback has a positive relationship with patient adaptation.*

Corrective feedback is also important for adaptation. It aims at correcting behaviors that may have led to the discrepancy and/or providing insights on how to reduce it. Corrective feedback directs attention to learning processes and focuses it on task details (Kluger and DeNisi 1996). For example, following a medical alert (e.g., high blood pressure), a CP may point out to a patient that this discrepancy can be avoided through physical activity or by reducing one's salt intake. Such feedback explicitly directs patients on how to adapt their behaviors to ameliorate their health condition, either by managing their own care or by seeking help. Hence, corrective feedback enables individuals to work strategically on the task (work smarter) by generating and confirming hypotheses on the means to reduce discrepancies (Kluger and DeNisi 1996).

While there is a lack of empirical evidence in healthcare settings, several laboratory studies have documented a positive effect of corrective feedback on individual task performance (e.g., Earley et al. 1990; Landsberg et al. 2010). There are also some contradicting results. In a field study of customer service employees, Waldersee and Luthans (1994) found that corrective feedback did not increase the performance of simple tasks. However, the authors attributed the nonsignificant result in part to a potential bias of the data analysis method.

Of note, feedback intervention theory predicts that for familiar tasks, corrective feedback may actually harm performance. This is because drawing attention to the details of a familiar task being performed can interfere with the execution of automatic scripts, leading to poor performance (Kluger and DeNisi 1996; Vallacher and Wegner 1987). However, this negative effect occurs when feedback pertains to a current activity being performed at that very moment (premise #5). In our case, even though some of the adaptations elicited by the feedback may be familiar to patients, we argue that the negative effect is unlikely to occur. There is a delay in feedback provision because patient readings are taken on a daily basis and are first prioritized and filtered by CPs before patients are contacted. Thus, the feedback is not necessarily linked to a specific focal task (see premise #1) and as such, is unlikely to disrupt performance.

H7: Corrective feedback has a positive relationship with patient adaptation.

We also expect a positive interaction effect between outcome and corrective feedback. Outcome feedback signals a discrepancy in performance and provides information on how the current situation compares to past results (i.e., the trend). This makes individuals aware of a goal discrepancy, signals a need for action, and predisposes them to take corrective action (Erez 1977; Kluger and DeNisi 1996). Corrective feedback can augment the effect of outcome feedback by directing effort toward adapting behavior and accomplishing the goal (Kayande et al. 2009). The synergistic effect is created because outcome and corrective feedback reinforce each other by providing both motivation to act and guidance as to how to act and what to do, both of which, taken together, are expected to lead to increased adaptations. For example, following an alert for a high blood pressure reading, a CP may review the results of previous readings with the patient (outcome feedback) and provide guidelines (corrective feedback) on how to reduce blood pressure (e.g., consuming less sodium). Patients will thereby learn how to direct their efforts and put their motivation into adaptive actions (patient adaptation). The feedback literature supports this argument and shows that a combination of outcome and process feedback strengthens the impact of the feedback on individual learning and performance (Goodman 1998; Kayande et al. 2009; Korsgaard and Diddams 1996). Hence,

H8: Corrective feedback has a positive moderation effect on the relationship between outcome feedback and patient adaptation.

Feedback intervention theory suggests that negative feedback can also direct attention at the upper (self-related) level, which has positive or negative effects depending on the nature of the feedback and task. In general, repeated exposure to negative discrepancies regarding issues (such as health-related results) can be emotionally taxing and undermine the individual's sense of confidence (Ilgen et al. 1979; Kluger and DeNisi 1996). Thus, attention can be diverted to self-related aspects (e.g., questioning one's efficacy) instead of focusing on the conditions that produced the discrepancy. Such attention diversion is especially acute when the feedback is perceived as self-threatening (e.g., blame). However, the theory stipulates that when the feedback is designed to be constructive and to foster self-efficacy (and the task is important and relatively simple), attention is redirected at the intermediate level and motivational processes are activated. Hence, performance is expected to improve (DeNisi and Kluger 2000).

Personal feedback that focuses on the feedback receiver's needs can address these issues. Personal feedback shows emphatic concern, has a considerate and nonthreatening tone, and projects confidence and hope toward attaining one's goals (Fong et al. 2018). It conveys to feedback receivers that feedback providers understand their challenges and want what is best for them (Young et al. 2017). It also helps to mitigate the adverse cognitions (e.g., doubt, low self-efficacy), emotions (e.g., anxiety, frustration), and self-protective processes (e.g., feedback rejection) that often come with receiving negative feedback (Ilgen and Davis 2000; O'Malley and Gregory 2011). By alleviating the adverse conditions and enabling patients to believe in the eventual success of regulating their behavior, patients can focus and redirect their attention at the intermediate (focal task) level and mobilize efforts to reduce the discrepancy. Patients thus feel empowered to take steps to manger their own care, or to seek help from their support network.

Empirical support for this relationship exists in organizational and health care settings. For example, a study of feedback giving by organizational leaders found that negative feedback that conveyed emphatic concern was associated with more positive emotions and higher perceived effectiveness (Young et al. 2017). Similarly, Bandura (2005) examined patient self-regulation in health care settings and suggested that patients with doubts about their efficacy benefited from the personal guidance and support of their care providers. There is also evidence that personal feedback provides a source of motivation for chronically ill patients to adapt their health behaviors (Jones et al. 2014; Song et al. 2014). Accordingly, we hypothesize:

H9: Personal feedback has a positive relationship with patient adaptation.

Patient Adaptation and Calls to 911

We suggest that patient adaptation will be negatively related to the likelihood of an individual to call an emergency ambulance (911) to signal a chronic disease-related health issue that may require transport to a hospital or emergency room. This relationship is outside the scope of feedback intervention theory. However, it is important to include because it aligns with the goals of telemonitoring programs of enabling patients to manage their own care while reducing the burden on the health care system.

First, patient adaptation resulting from CP feedback can entail an increased ability of patients to manage their own chronic conditions (i.e., changing a behavior that created the discrepancy or implementing a behavior to reduce the discrepancy), thereby reducing the need to call 911. For example, COPD patients might implement pursed-lip or diaphragmatic breathing to reduce breathlessness. There is qualitative evidence suggesting that a patient's decision to call 911 is determined largely by the perceived failure to manage the situation by oneself (i.e., lack of adaptation) (Ahl et al. 2006; Olsson and Hansagi 2001).

Second, individual adaptation can also involve cognitive or learning effects (Barki et al. 2007). As such, patients can learn through the feedback from CPs *when* it is appropriate (or not) to call 911. Qualitative studies investigating the reasons chronically ill patients call 911 attributed the calls to patients' lack of understanding about the appropriate use of the service (e.g., Ahl et al. 2006; Dejean et al. 2016). Moreover, patients learn *where* to seek help when needed. Rather than reactively calling 911, patients with access to a feedback ecosystem can proactively reach out to providers within the ecosystem. Chronically ill patients have been found to call 911 frequently as a way to emphasize their need for care, even when the situation was not urgent (Ahl et al. 2006). By adapting and learning where to seek help, such needs can be fulfilled by the feedback ecosystem, rather than by taxing the emergency response system. Accordingly,

> *H10: Patient adaptation has a negative relationship with calls to 911.*

Method

Study Setting

The study is conducted in the context of a telemonitoring system that transmitted patient health-related data from a patient's home to providers (CP) through the use of at-home medical devices: blood pressure manager, body manager (weight scale), SpO2 manager (pulse oximeter) and glucomanager. The devices recorded the daily readings of patients and transmitted them via a cellular network to a proprietary health tracking and information system (IdealLife®; www.ideallife.com).

The home telemonitoring system was managed by the Community Paramedic Remote Patient Monitoring program (CPRPM), which established program guidelines, funding structures, technology support, documentation, and training procedures. All CPs received training on the standardized patient-related goals (i.e., patients managing their care and knowing when to seek help), the procedure for onboarding patients, as well as on how to use the alert system and devices. The patient onboarding procedure was conducted through a home visit where CPs discussed the goals of the program with the patients and trained them on how to use the devices.

Data and Empirical Approach

Our study employed a prospective cohort design. The data set included 212 chronically ill patients who participated in the 26-week duration of the CPRPM program. Males comprised 44% of the patients, and the average age of the patients was 75.6 years. The key criterion for inclusion was patients with a diagnosis of CHF and/or COPD who had experienced multiple exacerbations from their condition (e.g., more than three 911 calls or two emergency room visits) within the 12 months prior to the program.

The telemonitoring system generates two types of alerts: (1) compliance alerts when no readings have been recorded within a 24-hour period, and (2) medical alerts when one or more readings of blood pressure, weight, oxygen saturation, ore blood glucose are outside the thresholds established by the patient's physician. Both types of alerts are logged in the system's task manager tool used by the provider (CP). For medical alerts, the system records the date an alert was activated, the threshold that triggered the alert (e.g., SpO2 less than 88 % for two consecutive readings, weight increase of 1 kg.), and the actual reading (e.g., SpO2: 87, weight: 59.2 kg.). Table 1 shows details of the alerts by patient condition.

The CPs followed on the alerts very closely and quickly decided whether or not a given alert needed to be activated.[3] For the activated alerts, the CP in most cases (86%) generated notes in the system indicating whether or not feedback was provided to the patient, what type of feedback was given, as

[3]The decision to activate an alert was influenced by the CP's knowledge of external information (e.g., patient on vacation) or previous alerts (i.e., a reading outside the threshold but deemed normal for a patient during that time).

Table1. Alerts by Patient Condition

Condition	COPD	CHF	Both	Total
# of Patients	105	80	27	212
Average Weekly # of Compliance Alerts (Min-Max)	3.18 (0-28)	5.85 (0-28)	4.52 (0-28)	4.53 (0-28)
Average Weekly # of Medical Alerts (Min-Max)	1.17 (0-73)	2.22 (0-111)	3.86 (0-35)	1.88 (0-111)

well as the resulting patient adaptation, if any. Cases for which no notes were generated for the activated alerts were considered missing data. Missing data due to missing or unclear notes were present in 14% of the activated alerts (19% for medical alerts, 1% for compliance alerts).[4] As CPs activated 68% of medical alerts and 11% of compliance alerts, follow-up interviews with nine CPs were conducted. The interviews suggested that, as we theorized, compliance alerts seemed to provide lower information value than medical alerts. One CP noted that compliance alerts "*just keep coming up. And that is one area that I didn't activate a lot of alerts as religiously as I did medical alerts*". Appendix C shows the distribution of alerts and notes recorded in the system.

Content Analysis

Because evidence of CP feedback and adaptations were embedded in the CP's qualitative text comments (i.e., notes), they were quantified with content analysis. Content analysis has been used in IS research (e.g., Pavlou and Dimoka 2006) to systematically code relevant information embedded in text comments into quantitative data to ensure the data analysis is objective and reliable. Numerical values of 1 (evidence of feedback or adaptation), 0 (evidence of no feedback or no adaptation), and missing (evidence unclear) were used to quantify the three types of feedback (outcome, corrective, and personal) and the patient adaptations.

One author completed pilot coding for five randomly chosen patients (186 notes) to ensure notes contained content that could be used to quantify the types of feedback inherent in feedback intervention theory. Detailed content analysis instructions were created and a second coder was introduced to the theory and trained in the content analysis procedure. Both coders repeated the analysis for another 12 randomly chosen patients (409 notes) and met to compare results and discuss discrepancies. A more comprehensive set of instructions was created that included examples of text comments to be used as a reference during the actual coding procedure. To ensure consistency, one coder (the first author) analyzed all 7,965 notes as well as an additional 8% duplicate notes (636) for calculating Holsti's (1969) intracoder reliability over a 4-week period (275 notes per day). The second coder analyzed notes from 31 randomly chosen patients (646 notes) for calculating Krippendorff's (1980) alpha, which is deemed a highly relevant measure of agreement among multiple coders.

We calculated frequencies and the two reliability scores for the three types of feedback and for patient adaptation (Appendix D). The range of our Krippendorff (0.903–0.970) and Holsti (0.973–0.992) reliability scores exceeded the minimum threshold values of 0.70 and 0.90, respectively. Because all reliability scores well exceeded the recommended values, the coding scheme is deemed reliable and we conclude that the results support the four proposed categories.

Coding of Feedback and Patient Adaptation

Appendix E shows a sample of patients (ID), alerts, related feedback notes, and patient adaptations. *Outcome feedback* was classified if the note contained feedback on a patient's health result (i.e., a discrepancy in results). Sample notes illustrate that outcome feedback provides patients with information on how readings compare to past trends. *Corrective feedback* was classified if the note reflected feedback on managing discrepancies in the patient's results. The feedback highlighted problems related to how the patient was managing their condition and offered recommendations for correction. The sampling of corrective feedback notes highlights a range of corrective feedback provided by CPs including proper use of the telemonitoring devices, behavioral modification (e.g., more exercise, nutrition), and medication management. While outcome feedback had information to help the patient understand past readings and behaviors, corrective feedback provided information to help correct future behaviors.

[4]The higher percentage of missing medical alert data (19%) may have been due to the noting system, which was open text with no data entry control in place. By contrast, the noting system for compliance alerts was a drop-down list that required users to enter data. The 1% missing compliance alert data (25 activated alerts) were early in the program before the control was added to the system. Because the probability of a missing note was not directly related to whether or not feedback was provided, we argue that our missing data are missing at random (MAR). Our interviews showed that not creating notes was often associated with factors such as forgetfulness or being too busy, "*When things are busy, I make sure I respond to an alert but either forget or don't have time to note it.*" Moreover, the analysis approach we used, namely generalized linear mixed modeling (GLMM), is robust for handling models with MAR data (Ibrahim and Molenberghs 2009).

Personal feedback was classified if the note reflected the CP's concern about the personal day-to-day routine of the patient or the patient's mood or attitude. Feedback was non-threatening in that it encouraged general well-being (e.g., eating three meals a day) or validated patient frustrations (e.g., doctors are too busy) or beliefs (e.g., going to church). Feedback also reassured patients that they were not doing anything wrong when they were feeling anxious or concerned about adhering to task goals related to their program. Finally, *patient adaptation* was assessed via communication interactions (in our case, measured through the CP notes), in which evidence is provided that adaptations have taken place. Adaptations included adaptive behaviors (e.g., visits to the doctor or other health professional to address a potential concern or issue, patients taking action to alter a problematic reading by laying down to relax, putting their feet up, using pursed breathing, etc.), as well as evidence of learning (Barki et al. 2007).

Measures

Table 2 summarizes the measures and descriptive statistics of the key variables of our model. Although the telemonitoring system captured daily patient data, we aggregated the daily measures to the weekly level. This was done to account for relatively short lags (typically a few days) between the different stages in the feedback ecosystem. Delays can exist between activating an alert and creating a note (e.g., when a CP is unable to contact a patient and tries again later or the next day). Sometimes there were lags between the feedback provided and the corresponding adaptation. These lags were captured in the note, which allowed us to match feedback to adaptations through the patient ID and date. Therefore, the daily level can some-times be too fine-grained a window to observe the patterns of relationships between alerts, feedback, and adaptation. By rolling up the values to the weekly level, we ensure better matching between these events. Our data and follow-up inter-views with CPs confirmed that 91% of alerts are handled and converted into feedback and adaptations on a weekly basis.

A second reason for choosing the weekly level is that the focus of our study is not at the episodic level. That is, we are not looking at whether a specific interaction between a provider and a patient leads to a particular adaptation. Instead, we are interested in the provision of different types of feedback over time and whether such feedback is associated with an increased number of adaptations in patients. We thus wanted to cast a net that would allow us to observe what happens when feedback is provided repeatedly over a certain period of time. The weekly model we test aligns well with the goals of our study, and allows us to answer whether for a CP having weeks with a higher (lower) frequency of alerts is associated with a higher (lower) frequency of feedback, and whether for a patient having weeks with a higher (lower) frequency of feedback provided is associated with a higher (lower) frequency of adaptation.

Medical and compliance alerts were weekly counts aggregated from the daily measures logged in the system. The three feedback variables (outcome, corrective, personal) and patient adaptation were also count variables that were aggregated from the daily measures. The final dependent variable in the model, calls to 911, is measured objectively using data captured from the centralized 911 call and transport database. CPs code 911 calls by incident type (e.g., clinical exacerbations, falls, injuries) and only 911 calls related to chronic disease exacerbations were included in the study. We aggregated this variable to the weekly level by using a collection of independent Bernoulli trials to model the likelihood of a patient calling 911 in a given week. We also treated time as a continuous variable and included the following control variables: gender, age (in years), geography (patient living in a rural or urban geographic area), and comorbidities, a measure of the severity of a patient's chronic condition (Sin et al. 2006).

Data Analysis

Our data set has a hierarchical structure, with 26 weekly measurements taken for each of a total of 212 patients. As our response variables were non-normal, we used generalized linear mixed modeling (GLMM) to analyze the data (Im et al. 2016). Using Proc Glimmix in SAS 9.4, we estimated a Poisson residual distribution (with a log link function) for the feedback and adaptation variables and a binomial residual distribution (with a logit link function) for calls to 911. We fitted a random intercept for each patient and an autoregressive covariance structure for the repeated measures. Our models showed no evidence of over-dispersion.

Results

Tables 3 through 7 summarize the results for each dependent variable. Model 1 includes the control variables, model 2 adds the main predictors, and model 3 adds the time effects, the lagged effects for the predictors, as well as the autoregressive and cross-lagged effects. The tables also report the variance components at both levels. As shown in Table 3 (model 3), medical alerts had a significant effect ($\beta = 0.106$, $p < 0.0001$), indicating that, holding other variables constant, a one-unit increase in medical alerts is associated with an increase in outcome feedback frequency by 11% ($e^{0.106} = 1.112$).

Table 2. Variable Measurement and Descriptive Statistics

Variable	Description [Measurement]	Mean [Freq]	STD	Min	Max
Observation-Level Variables (Level 1)					
Week	Time identifier [Continuous variable]	–	–	1	26
MedAlerts	Medical alerts [Count variable aggregated at weekly level]	1.88	4.15	0	111
CompAlerts	Compliance alerts [Count variable aggregated at weekly level]	4.53	6.88	0	28
FeedOut	Outcome feedback [Count variable aggregated at weekly level]	0.17	0.47	0	4
FeedCorr	Corrective feedback [Count variable aggregated at weekly level]	0.32	0.70	0	7
FeedPers	Personal feedback [Count variable aggregated at weekly level]	0.37	0.77	0	7
PatAdapt	Patient adaptation [Count variable aggregated at weekly level]	0.09	0.34	0	3
Calls911	Patient calls to 911 [Binary variable. We used independent Bernoulli trials to model the likelihood of a patient calling 911 on a given week]	[n(0)=5204; n(1)=308]		0	1
Patient-Level Variables (Level 2)					
Gender	Gender of patient [Binary variable (1= if male)]	[n(0)=119; n(1)=93]		0	1
Age	Age of patient in years [Continuous variable]	75.60	12.63	31	100
Geography	Geographic location where patient lives (urban vs. rural) [Binary variable (1 = if urban)]	[n(0)=22; n(1)=190]		0	1
Co-morbidities	Number of existing co-occurring chronic illnesses in addition to patient's primary condition diagnosed prior to program admission [Ordered categorical variable (0= no co-occurring conditions to 1= 1 co-occurring condition)]	[n(0)=185; n(1)=27]		0	1
EMS Service-Level Variables (Level 3)					
EMS	Emergency medical service (EMS), each in a geographic location and employing a number of CPs [Categorical variable (1=EMS1 to 9=EMS9)]	[n(1)=6; n(2)=9; n(3)=81; n(4)=33; n(5)=5; n(6)=6; n(7)=9; n(8)=19; n(9)=44]		1	9

Freq = frequency; STD = standard deviation; n(): frequency of a given value for a categorical variable.

Table 3. Coefficient Estimates for Outcome Feedback

		Model 1	Model 2	Model 3
	Intercept	-1.806** (0.612)	-2.810*** (0.553)	3.172*** (0.591)
Patient-Level Controls	Gender	-0.040 (0.167)	0.068 (0.005)	-0.019 (0.157)
	Age	0.001 (0.007)	0.007 (0.006)	0.006 (0.006)
	Geography	0.430 (0.287)	0.464 (0.254)	0.630* (0.272)
	Comorbidities	0.537* (0.242)	0.515* (0.206)	0.478* (0.212)
Main Predictors	MedAlerts		0.064*** (0.005)	0.106*** (0.012)
Time Effects	Weeks	-0.048*** (0.005)	-0.045*** (0.005)	-0.036*** (0.006)
	MedAlerts*Weeks			-0.003*** (0.001)
Lag Effects	MedAlerts (-1 week)			0.005 (0.008)
	MedAlerts (-2 weeks)			0.004 (0.008)
Autoregressive & Cross-Lagged Effects	FeedOut (-1 week)			0.019 (0.049)
	PatAdapt (-1 week)			-0.024 (0.072)
	Calls911 (-1 week)			-0.037 (0.149)
Variance Components	Intercept Variance (Patient)	1.142 (0.146)	0.763 (0.110)	0.840 (0.124)
	Residual Variance	1.126 (0.023)	0.844 (0.017)	0.787 (0.017)
	Residual Covariance (AR1)	0.079 (0.023)	0.056 (0.017)	0.043 (0.021)

*p < 0.05; **p < 0.01; *** p < 0.001; standard error in parentheses.

H1 was thus supported. Two control variables were significant. Urban patients received 88% more outcome feedback than rural patients, and comorbid patients (COPD and CHF) received 61% more outcome feedback than those with only one disease. The lagged, cross-lagged, and autoregressive effects were nonsignificant. There were significant time effects; every week was associated with a 3.5% decrease in outcome feedback frequency ($e^{-0.036} = 0.965$). The frequency decreased by 60% over the 26-week life of the program ($0.965^{26} = 0.396$). Also, there was a small but significant time-alert interaction (every week the effect of medical alerts on outcome feedback frequency decreased by 0.3%).

For corrective feedback, medical alerts had a positive effect (8% increase in corrective feedback for a one-unit increase in medical alerts) and compliance alerts had a significant curvilinear effect. H2 and H4 are thus supported. The only significant control variables were geography (79% more corrective feedback for urban patients) and comorbidities (57% more corrective feedback for comorbid patients). Time had significant effects. We found a 2.1% week-on-week (42% overall) decrease in corrective feedback. The week-on-week effects of alerts on corrective feedback decreased by 0.2% for medical alerts and by 0.3% for compliance alerts. The lagged, cross-lagged, and autoregressive effects were all nonsignificant (see Table 4).

For personal feedback, medical alerts had a significant effect ($\beta = 0.080$, $p < 0.0001$), indicating that, holding other variables constant, a one-unit increase in medical alerts is associated with an increase in personal feedback frequency of 8% ($e^{0.080} = 1.083$). H3 is thus supported. Compliance alerts had a significant positive linear effect with a negative curvature, thereby supporting the curvilinear effect hypothesized in H5. Two control variables were significant (urban patients received 76% more personal feedback than rural patients and comorbid patients received 51% more personal feedback than those with only one disease). The lagged, cross-lagged, and autoregressive effects were nonsignificant. Similar to the case of outcome feedback, the time effects were significant albeit less pronounced (2% week-on-week or 45% overall decrease in personal feedback, and every week the linear effects of medical and compliance alerts on personal feedback frequency decreased by 0.2% and 0.3%, respectively).

The results for patient adaptation are shown in Table 6. Outcome feedback was significant ($\beta = 0.528$, $p < 0.001$), with a 70% increase in patient adaptation per unit increase in outcome feedback. H6 was supported. However, corrective feedback was not significantly related to patient adaptation ($\beta = -0.083$, $p = 0.508$). H7 was not supported. Surprisingly, the interaction effect of outcome and corrective feedback was significant but in the opposite (negative) direction ($\beta = -0.246$, $p < 0.001$). H8 was not supported. The interaction plot (Figure 3) shows that the positive effect of outcome feedback on adaptation decreases at increasing levels of corrective feedback. Personal feedback was significant ($\beta = 0.595$, $p < 0.001$), indicating an 81% increase in patient adaptation per unit increase in personal feedback (with other variables held constant). H9 was thus supported. Further, two control variables were significant: urban patients (geography) and patients with comorbidities were associated with higher levels of adaptation (103% and 197%, respectively). Time had a significant effect. Patient adaptation increased by 3.8% week-on-week, amounting to a 162% increase over the program duration. The two-week lagged effect of corrective feedback was negative, and the one-week and two-week lags of personal feedback were positive.

As shown in Table 7, we found a negative and significant association between patient adaptation and calls to 911 ($\beta = -1.101$, $p < 0.05$), indicating that a one-unit increase in adaptation is associated with a decrease in the odds of calling 911 by 67% ($e^{-1.101} = 0.33$). H10 was thus supported. One control variable was significant (the odds of calling 911 were 2% lower for a one-unit increase in age), and there was a significant interaction between time and patient adaptation. The lagged and autoregressive effects were nonsignificant.

Post Hoc Analyses

To explore the mediating effects of CP feedback, we conducted mediation analyses using generalized structure equation modeling (GSEM) in Stata, which allows for estimating the indirect effects in multilevel models with nonlinear response variables (Preacher 2015). We found that all five indirect effects of the alerts on adaptation are significant (see Appendix F).

Because Proc Glimmix is limited to testing two levels of random effects (i.e., time and patient effects), we were unable to measure random effects at the EMS service level. However, we conducted *post hoc* tests to measure the fixed effects across the nine paramedic services. We found significant differences in the frequency of feedback provided, especially for EMS Service 4 (686% more outcome feedback, 288% more corrective feedback, and 360% more personal feedback, as compared to EMS Service 1). Other EMS services (EMS2, EMS3, EMS5, EMS8, and EMS9) had significant relationships with only some of the feedback types. There was no difference in patient adaptation or odds of calling 911 across the nine services. Importantly, when controlled for paramedic service, the significance and directionality of the predictors remained consistent against our previous models, suggesting that our previous results are robust.

Table 4. Coefficient Estimates for Corrective Feedback

		Model 1	Model 2	Model 3
	Intercept	-0.916 (0.502)	-1.548*** (0.448)	-1.891*** (0.475)
Patient-Level Controls	Gender	-0.028 (0.140)	-0.075 (0.123)	-0.117 (0.129)
	Age	-0.002 (0.006)	0.001 (0.005)	-0.001 (0.005)
	Geography	0.445 (0.236)	0.478* (0.207)	0.581** (0.220)
	Comorbidities	0.493* (0.201)	0.450** (0.174)	0.452* (0.182)
Main Predictors	MedAlerts		0.056*** (0.004)	0.080*** (0.010)
	CompAlerts		0.056*** (0.015)	0.103*** (0.019)
	(CompAlerts)^2		-0.004*** (0.001)	-0.004*** (0.001)
Time Effects	Weeks	-0.049*** (0.004)	-0.043*** (0.004)	-0.021*** (0.006)
	MedAlerts*Weeks			-0.002* (0.001)
	CompAlerts*Weeks			-0.003*** (0.001)
Lag Effects	MedAlerts (-1 week)			0.004 (0.007)
	CompAlerts (-1 week)			0.002 (0.008)
	MedAlerts (-2 weeks)			-0.004 (0.007)
	CompAlerts (-2 weeks)			-0.002 (0.007)
Autoregressive & Cross-Lagged Effects	FeedCorr (-1 week)			0.001 (0.029)
	PatAdapt (-1 week)			0.014 (0.059)
	Calls911 (-1 week)			-0.069 (0.120)
Variance Components	Intercept Variance (Patient)	0.793 (0.098)	0.560 (0.077)	0.608 (0.085)
	Residual Variance	1.262 (0.026)	0.738 (0.015)	0.897 (0.019)
	Residual Covariance (AR1)	0.112 (0.015)	0.074 (0.019)	0.051 (0.021)

*p < 0.05; **p < 0.01; ***p < 0.001; standard error in parentheses.

Table 5. Coefficient Estimates for Personal Feedback

		Model 1	Model 2	Model 3
	Intercept	-0.7655 (0.479)	-1.3697*** (0.412)	-1.759*** (0.444)
Patient-Level Controls	Gender	-0.005 (0.134)	-0.019 (0.115)	-0.074 (0.121)
	Age	0.002 (0.005)	0.002 (0.003)	0.0005 (0.005)
	Geography	0.375 (0.223)	0.405 (0.192)	0.567** (0.205)
	Comorbidities	0.491* (0.191)	0.448* (0.163)	0.412* (0.170)
Main Predictors	MedAlerts		0.054*** (0.003)	0.080*** (0.009)
	CompAlerts		0.051*** (0.014)	0.093*** (0.018)
	(CompAlerts)^2		-0.004*** (0.003)	-0.004*** (0.001)
Time Effects	Weeks	-0.050*** (0.004)	-0.043*** (0.003)	-0.023*** (0.005)
	MedAlerts*Weeks			-0.002** (0.001)
	CompAlerts*Weeks			-0.003*** (0.001)
Lag Effects	MedAlerts (-1 week)			0.003 (0.006)
	CompAlerts (-1 week)			0.009 (0.008)
	MedAlerts (-2 weeks)			0.004 (0.006)
	CompAlerts (-2 weeks)			-0.005 (0.007)
Autoregressive & Cross-Lagged Effects	FeedPers (-1 week)			-0.003 (0.026)
	PatAdapt (-1 week)			0.020 (0.054)
	Calls911 (-1 week)			-0.072 (0.110)
Variance Components	Intercept Variance (Patient)	0.730 (0.090)	0.501 (0.067)	0.536 (0.074)
	Residual Variance	1.26 (0.026)	0.951 (0.019)	0.914 (0.019)
	Residual Covariance (AR1)	0.138 (0.015)	0.085 (0.015)	0.067 (0.022)

*p < 0.05; **p < 0.01; ***p < 0.001; standard error in parentheses.

Table 6. Coefficient Estimates for Patient Adaptation

		Model 1	Model 2	Model 3
	Intercept	-4.264*** (0.766)	-4.782*** (0.696)	-4.931*** (0.701)
Patient-Level Controls	Gender	0.102 (0.206)	0.105 (0.186)	0.097 (0.186)
	Age	0.001 (0.008)	0.001 (0.007)	0.001 (0.007)
	Geography	0.791* (0.377)	0.722* (0.344)	0.709* (0.348)
	Comorbidities	1.271*** (0.270)	1.119*** (0.241)	1.088*** (0.238)
Main Predictors	FeedOut		0.629*** (0.109)	0.528*** (0.111)
	FeedCorr		0.100 (0.124)	-0.083 (0.125)
	FeedOut*FeedCorr		-0.266*** (0.043)	-0.246*** (0.044)
	FeedPers		0.458*** (0.118)	0.595*** (0.119)
Time Effects	Weeks	0.017** (0.006)	0.035*** (0.006)	0.037*** (0.006)
	FeedOut*Weeks			0.019 (0.011)
	FeedCorr*Weeks			0.010 (0.014)
	FeedPers*Weeks			-0.001 (0.016)
Lag Effects	FeedOut (-1 week)			0.070 (0.079)
	FeedCorr (-1 Week)			-0.180 (0.114)
	FeedPers (-1 week)			0.377** (0.127)
	FeedOut (-2 weeks)			0.123 (0.081)
	FeedCorr (-2 weeks)			-0.239* (0.107)
	FeedPers (-2 weeks)			0.340** (0.120)
Autoregressive & Cross-Lagged Effects	PatAdapt (-1 week)			0.032 (0.059)
	Calls911 (-1 week)			-0.035 (0.163)
Variance Components	Intercept Variance (Patient)	1.311 (0.199)	1.010 (0.165)	0.982 (0.163)
	Residual Variance	0.677 (0.014)	0.609 (0.012)	0.575 (0.012)
	Residual Covariance (AR1)	0.125 (0.015)	0.117 (0.015)	0.103 (0.020)

*p < 0.05; **p < 0.01; ***p < 0.001; standard error in parentheses.

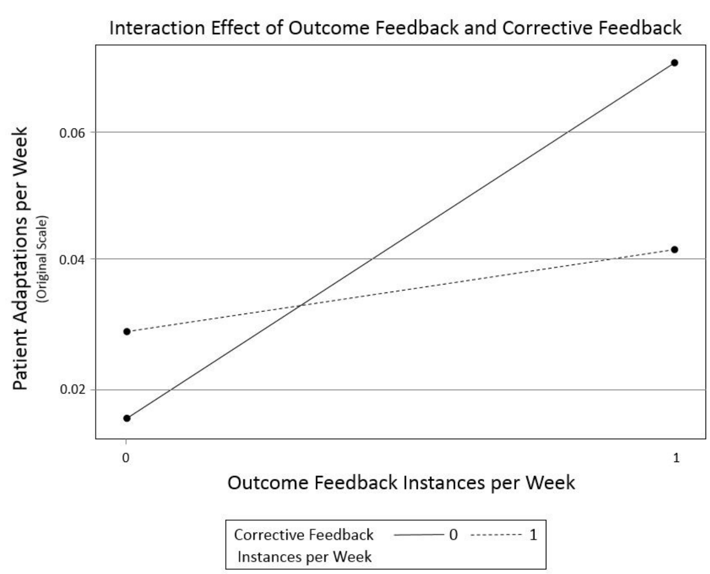

Figure 3. Interaction Plot

Table 7. Coefficient Estimates for 911 Call Events

		Model 1	Model 2	Model 3
	Intercept	-1.106 (0.622)	-1.060 (0.623)	-1.226 (0.666)
Patient-Level Controls	Gender	-0.147 (0.179)	-0.146 (0.179)	-0.157 (0.192)
	Age	-0.020** (0.007)	-0.020** (0.007)	-0.022** (0.007)
	Geography	-0.217 (0.281)	-0.214 (0.282)	-0.083 (0.312)
	Comorbidities	-0.041 (0.268)	-0.030 (0.269)	-0.199 (0.294)
Main Predictor	PatAdapt		-0.069 (0.188)	-1.101* (0.465)
Time Effects	Weeks	-0.002 (0.008)	-0.002 (0.008)	-0.008 (0.008)
	PatAdapt*Weeks			0.055* (0.025)
Lag Effects	PatAdapt (-1 week)			0.273 (0.147)
	PatAdapt (-2 weeks)			0.115 (0.152)
Autoregressive Effects	Calls911 (-1 week)			0.151 (0.161)
Variance Components	Intercept Variance (Patient)	0.894 (0.161)	0.895 (0.161)	1.083 (0.181)
	Residual Variance	0.945 (0.019)	0.945 (0.019)	0.656 (0.014)

*p < 0.05; **p < 0.01; ***p < 0.001; standard error in parentheses.

Discussion

While telemonitoring technologies can provide benefits to chronic disease patients, our understanding of their effects is limited. We complement the feedback literature by examining the effects of a telemonitoring feedback ecosystem (comprised of technology, care providers, and patients) on the behavioral patterns of chronically ill patients. The ecosystem focuses on socially mediated behavior regulation, with feedback cascading through two stages. In the first stage, technology tracks and analyzes daily readings, then conveys alerts to CPs. In the second stage, CPs respond to alerts by giving feedback (outcome, corrective, personal) to the patients.

Our results show what types of feedback are relevant for each stage and how they are related to provider and patient actions. Overall, eight of our ten hypotheses were supported. Medical alerts seem to signal urgency to the CPs and offer a high information value. Medical alerts had a positive association with all three types of CP feedback (outcome, corrective, and personal). By contrast, compliance alerts had curvilinear relationships with corrective and per-sonal feedback. This suggests that with compliance alerts, providers might suffer from an alert fatigue effect similar to the one found in the computerized drug alerts literature (Glassman et al. 2006; Tamblyn et al. 2012). Our results also show that the behavioral regulation of patients (i.e., how they respond and adapt to feedback) is based on attributes of the feedback. As hypothesized, repeated exposures to outcome and personal feedback were associated with increases in patient adaptations. In turn, patient adaptation was negatively related to the odds of calling 911. The fact that the adapta-tions we examined were relatively straightforward and still resulted in a decrease in 911 calls has important implications for improving the efficiency of healthcare systems using simple feedback and adaptation techniques.

Two hypotheses were not supported. First, corrective feedback had a nonsignificant relationship with patient adaptation. While this finding is contrary to our expectation, it is consistent with results from field studies that did not find positive effects of corrective feedback (e.g., Lekwa et al. 2018; Mikami et al. 2010; Waldersee and Luthans 1994). This result might be explained by the possibility that the corrective feedback provided might not have activated attention strongly enough to change patient behaviors. As we discussed earlier, feedback intervention theory stipulates that goals are organized hierarchically (abstract self-goals, task goals, task detail goals). It is possible that the patients did not map the lower-level goals activated by corrective feedback (e.g., elevate feet, go for a walk) into higher-level goals. As an example from our content analysis, one CP noted, "*Patient feels a little sluggish the last few days and weight is up a bit. He was encouraged to get some potassium (i.e., eat bananas)*." In this example, the feedback (eat bananas) is focused on task details that the patient may not associate with their higher-level goals (decreasing sluggishness and weight). Thus, the feedback's information value might not have been high enough to sustain attention on required changes.

Another possibility is that repeated corrective feedback was perceived as controlling by the patients. There is evidence suggesting that ongoing feedback from a source decreases satisfaction and perceived autonomy as a result of feeling intensely monitored (Ilgen et al. 1979; Waldersee and Luthans 1994). Further, feedback is less likely to be effective when it undermines an individual's sense of control and autonomy (Ilgen and Davis 2000; Kluger and DeNisi 1996; Shute 2008). In our case, the notions of monitoring and adherence to taking daily readings and healthy behaviors (e.g., eating well, exercise) were all inherent in the program's design but new to many patients' daily routines. As such, being repeatedly told what to do may have reduced patients' perceived control and subsequent adaptation efforts.

A third explanation could be that the patients did not accept corrective feedback from the CP in the same way as they would from a primary care physician. In other words, they may not have perceived the CP as a credible source for telling them what to do and therefore rejected the corrective feedback message (Ilgen et al. 1979; Steelman et al. 2004). Therefore, an important question for future research is to examine whether CPs differ from other care providers in terms of how patients perceive, accept, and act on a CP's corrective feedback.

The second hypothesis that was not supported concerns the interaction effect between corrective and outcome feedback, which was significant but negatively related to patient adaptation. Feedback intervention theory suggests that outcome feedback regulates behavior by activating motivational processes (premise #5). Other theories of motivation distinguish between autonomous and controlled motivation and suggest that the latter can produce energy-depleted actions (Deci and Ryan 2008). In line with the autonomy argument, it is possible that when corrective feedback is repeatedly administered in addition to outcome feedback, the motivation of patients might switch from being mainly based on autonomy to one where they feel they are controlled, which can impede behavioral adaptation (Ryan and Deci 2000). This combination of feedback may thus limit and undermine the motivational effect of outcome feedback.

Finally, our results suggest that the feedback ecosystem progresses over time. Over the life of the telemonitoring program, there were changes in the frequency of actions observed for the three components of the ecosystem (technology, providers, patients). The frequency of technology alerts varied over the 26 weeks of our study: medical alerts decreased by 55% while compliance alerts increased by 120%.[5] We also found that CP feedback decreased over the period of our study (-61% for outcome feedback, -42% for corrective, -45% for personal). Interestingly, the amount of patient adaptation increased by 162% over the same period. Taken together, these results suggest that the telemonitoring feedback ecosystem was efficient and effective in allowing patients to better self-manage their care. The fact that compliance alerts increased over time is consistent with the literature, which shows that telemonitoring adherence decreases over time (e.g., Morlion et al. 2002; Paré et al. 2007). This may suggest that patients become less motivated to use the technology as they learn to adapt. The results suggest that integrating telemonitoring into a feedback ecosystem is important because over time, the care provider can reinforce, complement, and supplement the feedback provided by the technology.

Implications for Research and Practice

This paper has several implications for research and practice. Our conceptualization of cascading feedback via a feedback ecosystem and the examination of different feedback types as mediators between telemonitoring technology and patient-related outcomes have important implications for the chronic disease literature. We have shown that it is important to account for the feedback ecosystem, the different types of technology-generated alerts, and the nuanced role of feedback types. Our findings suggest that examining the nomological network of relationships that connect the telemonitoring technology with the actions of providers and patients can complement the prevailing techno-centric view and provides additional insights. Our work has implications for examining how different types of alerts and feedback function in different provider contexts (e.g., CPs, nurses, doctors) and for different chronic disease types.

Furthermore, this framework provides generalizable insights beyond monitoring patients with chronic disease (e.g., university systems where advisors give feedback based on student-related data captured by monitoring technologies; suicide prevention initiatives on social media). Whereas advances in computing and networking technologies make it easy to capture data and provide system-generated feedback directly to the feedback receiver (even in real time), our research suggests that feedback provided through two stages and mediated by a third party is valuable. One implication is that delivering repeated feedback directly to individuals who are not experts in interpreting and analyzing the feedback may overwhelm their cognitive resources and provide relatively low information value. In line with feedback intervention theory (premise #3), such feedback is less likely to channel attention in an effective way that benefits behavior regulation. But when the technology-generated feedback is first filtered and prioritized by experts and subsequently relayed to the feedback receiver in a way that they can understand and apply without overloading their attention, more promising results can be expected.

[5] We ran separate analyses to examine the frequency of providing medical and compliance alerts over time.

Our results also indicate that for the feedback to pass from the first stage (agent receives technology-generated feedback) to the second stage (agent provides feedback to receiver), it may need to offer a high information value. Repeated provision of feedback with a lower information value (in our case, compliance alerts) could result in a diminishing response over time.

A third insight is that some types of feedback can especially benefit from having the feedback mediated by external agents. Specifically, we found that patient adaptations increased as a result of personal feedback that projected a sense of care, appeared well-intentioned, was sensitive to the emotional and cognitive needs of the individual, and showed a pathway to improvement. While outcome and corrective feedback can potentially be automated and delivered directly to feedback receivers, it is much more difficult to automate personal feedback in an effective way. Our results thus have implications for research on automated and real-time feedback both in the healthcare context and beyond.

A fourth insight is that corrective feedback, while in theory easier to automate than personal feedback, may also benefit from being mediated by an external agent rather than provided electronically. Our unsupported hypotheses suggest that how cor-rective feedback is given and perceived by the feedback receiver might be key to determining whether or not it will result in the intended behavioral adaptations. We conjectured that whereas the corrective feedback was intended to be informational, it may have been perceived by the feedback receivers as controlling and therefore did not lead to effective behavior adaptation. Given that our study was not comparative, future research can examine whether providing corrective feedback in a way that promotes a dialogue and discusses options (i.e., informational) can be effectively automated or needs human mediation.

Our findings also have general implications for patients, providers, and policy makers. Telemonitoring technology is not a silver bullet. Our results would suggest that there are benefits in embedding the technology in a feedback ecosystem. Our results also indicate that alternative care providers (CPs in our study) could become a viable force in healthcare systems facing resource scarcity (Safavi and Dare 2018). Further, our findings indicate that simple interventions with a personal focus or ones that signal a discrepancy and provide a reference point can influence patient adaptations. Similarly, simple patient adaptations achieved through a technology-activated feedback ecosystem can lower the odds of 911 calls. This has important implications for the use of system resources given that there are over 250 million 911 callers in the United States each year (Langabeer et al. 2016).

Limitations and Future Research

Our study has some limitations and provides several opportunities for future research. First, one methodological limitation is that a pretest-posttest design with a control group was not feasible in our study. The nature of the dataset further precluded the use of instrumental variables to test for endogeneity. While our study design does not allow us to make strong causal inferences nor to have tight experimental manipulation of the study's variables, we employed Guide and Ketokivi's (2015) guidelines to rely on theoretical justification for addressing endogeneity when statistical tests are not possible. Thus, the use of feedback intervention theory in this study's model offers *a priori* grounding for the relationships between feedback and adaptation. Further, we included several robustness checks to increase confidence in our results (control variables, lagged independent variables, cross-lagged correlations, autoregressive effects). Nonetheless, the lack of a control group only allows us to infer associations rather than to claim causality. Whereas our study takes place in an actual clinical setting and provides high ecological validity and realism, there is an opportunity for future research to expand on our work by employing experimental designs and using instrumental variables to control for endogeneity.

Second, the adaptations we examined in the study were relatively simple and observed within blocks of one-week periods. While we found that these simple adaptations were related to a reduction in the odds of calling 911, there is an opportunity to examine the impact of longer-term adaptations that can be influenced by the telemonitoring-based feedback ecosystem. This will require tracking specific feedback episodes over longer periods of time.

Third, we focused on within-person differences and did not measure between-person psychological factors that moderate the behavioral consequences of feedback, such as individual differences or the nature of the relationship between patients and providers. For example, extensions to feedback intervention theory have looked at how the effects of feedback and self-regulation vary depending on whether individuals work under a promotion or prevention focus (DeNisi and Kluger 2000; Kluger and Van Dijk 2010). Examining regulatory focus and other fine-grained mediating and moderating variables opens up avenues for future research.

Future research can also extend our work by examining how the different types of feedback could eventually influence clinical outcomes. This would require looking at other predictors, mediating factors, and potentially longer-term time frames. Additionally, this study assessed the nature of the feedback-adaptation relationship in the context of an asynchronous system. Future research should thus also consider systems in which the alert–feedback–adaptation process occurs in closer succession to one another.

Conclusion

At a time of increasing chronic disease prevalence and challenges, telemonitoring technology can be key to enabling patients to manage their own care while reducing the burden on healthcare systems. Our study shows that there is value in embedding the technology in a feedback ecosystem made up of the technology, care providers, and patients. We explore some of the nuances of mediated feedback that cascades via two stages. We show that different types of technology alerts have different associations with the feedback given by care providers. We also find that different types of provider feedback are related in different ways to patient adaptation and ultimately to 911 call reduction. Patients with chronic illnesses adapt effectively to personal feedback and to feedback about how their current medical results compare with previous results. However, when they receive repeated feedback from CPs telling them what to do (corrective feedback), no corresponding increase in adaptation is observed, and corrective feedback can attenuate the benefits of outcome feedback. The present study advances our understanding of how telemonitoring can benefit patients with chronic disease. Our two-stage cascading feedback framework also contributes to feedback intervention theory and to broader research contexts that incorporate monitoring technologies with third-party mediated feedback. We hope that the ideas examined in this paper will stimulate further research on the topic.

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About the Authors

Kathryn Brohman is an Associate Professor and Distinguished Faculty Fellow of Management Information Systems (MIS) at the Smith School of Business, Queen's University (Canada). Prior to that, she was assistant professor at the Terry College of Business, University of Georgia. Kathryn holds a Ph.D. in MIS from the Ivey School of Business, Western University in Canada. Her research examines the impacts of data integration with a specific focus on customer and patient services and organizational control processes. Her research has been published in top-tier journals such as *MIS Quarterly*, *Journal of the Association for Information Systems*, *Information Systems Journal, Communications of the ACM,* and *MIS Quarterly Executive*.

Shamel Addas is an Assistant Professor and Distinguished Faculty Fellow of Management Information Systems (MIS) at the Smith School of Business, Queen's University (Canada). Prior to that, he was assistant professor at Ieseg School of Management in France. He holds a Ph.D. in Management from McGill University. Shamel's research examines the impacts of information technology (IT) use on individuals and groups in work-related and healthcare settings. His first stream of research focuses on the ambivalent consequences of IT use and, specifically, the impact of IT-mediated interruptions on work performance. The second stream of research investigates the use of healthcare information technologies (HIT) and its relationship with patient-related processes and outcomes. His research has been published or is forthcoming in top-tier journals such as *MIS Quarterly*, *Journal of Management Information Systems*, *MIT Sloan Management Review*, *Journal of the Association for Information Systems*, and *Information Systems Journal*. He has also presented his work at various academic conferences, including the Academy of Management, the International Conference on Informatoin Systems, America's Conference on Information Systems, and the Hawaii Intrnational Conference on System Science. Shamel won the Best Paper Award at the 2010 Human–Computer Interaction Workshop of the International Conference on Information Systems.

Jeff Dixon is a Ph.D. candidate at the Smith School of Business, Queen's University (Canada) and Vice-President–Higher Education Subject Matter Expert at Traction on Demand. He previously served as Associate Director, The Monieson Centre at Smith School of Business, leading research programs on the knowledge economy and healthcare transformation. His research investigates the relationship between data, analytics, user feedback, and digital transformation. He has published two books presented at numerous academic conferences and industry events. In 2017 he was awarded the Best Paper Award for Management Information Systems at the Administrative Sciences Association of Canada Conference.

Alain Pinsonneault, Fellow-Royal Society of Canada, member of the National Order of Québec, and Fellow of the AIS, is a James McGill Professor and the Imasco Chair of information systems in the Desautels Faculty of Management at McGill University. His current research interests include the organizational and individual impacts of information technology, user adaptation, business modeling in the digital economy, e-health, and the business value of IT. His research has appeared in numerous journals, including *Management Science, MIS Quarterly, Information Systems Research, The Journal of MIS, Decision Support Systems*, and *Organization Science*. He has served on the editorial boards of several journals including *MIS Quarterly, Information Systems Research, Organization Science,* and *The Journal of MIS.*

Appendix A

Feedback Intervention Theory and the Two-Stage Feedback Ecosystem

	Premises of Feedback Intervention Theory	Premises of our Feedback Ecosystem Framework
Premise #1: Behavior Regulation through Feedback-Goal Comparisons		
Goal setting	Internal or external (by other actors)	External (by physician and CP, and discussed with patient)
Basis of discrepancy	A specific activity, a focal task, or a general result	Patient's health result (vitals reading not taken or is discrepant from goal)
Mechanism of behavior regulation	Feedback	Feedback that cascades via two stages: Stage 1: Technology feedback (alert) given to CP to signal a discrepancy in patient's health result → Alert regulates the CP's feedback behavior Stage 2: CP feedback given to patient → Feedback regulates the patient's behavior adaptations to self-manage their care or to seek help
Source of feedback	External (humans and/or technology)	External: Telemonitoring technology in stage 1 and CP in stage 2
Outcomes of feedback	Adapting behavior is a typical response when goals are clear and feedback receiver is committed	Adapting behavior is expected (goals are clear, set by physician and CP, and discussed with patients who are committed to goals of improving their care)
Premise #2: Hierarchical Levels of Goal Organization		
Upper level	Meta-task (i.e., self-related) goals	Meta-task goals: higher quality of life for patients in the comfort of their home
Intermediate level	Focal task goals	Focal task goals: manage patient care (self-manage condition or seek help)
Lower level	Task detail goals	Task detail goals: Specific actions to manage patient care (e.g., administer supplemental oxygen, elevate feet)
Premise #3: Conditions for Discrepancies and Feedback to Receive Attention and Trigger Behavior Regulation		
Conditions for receiving attention	Discrepancy is salient and important	Health-related discrepancies are salient and important for both CP and patient with chronic disease (can have important health consequences)
	Feedback does not tax cognitive resources of feedback receiver	Stage 1: Alerts are filtered and prioritized by degree of severity to avoid overloading the CP Stage 2: CP feedback given to patient is prioritized, actionable, and given only when needed (patients have no direct access to the alerts)
	Feedback is presented in a way that can be easily interpreted by receiver	Stage 1: Alert details can be interpreted by medically trained CP Stage 2: CP feedback is customized and provided through two-way communication (i.e., phone, visit) to ensure patient understanding
	Feedback has high information value content	Stage 1: Medical alerts have high information value for CP (compliance alerts have lower information value) Stage 2: CP feedback has high information value for patient
Premise #4: Normal Focus of Attention		
Normal focus of attention	Attention is typically oriented at focal task or activity to maximize attentional efficiency	CP's and patient's attention are normally oriented at the level of their day-to-day tasks or activities (whether work related or personal)

[6]While we did not measure attention allocation, we assumed that commitment to health-related goals that were explicitly set would act as a proxy for attention focus and intention to pursue the goals (Johnson et al. 2006; Shah et al. 2002).

Premise #5: Effects of Feedback Interventions on Attention Focus and Behavior Regulation[1]		
(1) Effects of Negative Feedback at the Intermediate (Focal Task) Regulation Level		
Feedback operating at this level	Outcome feedback (knowledge of result, change in performance, velocity, etc.)	Two subtypes of outcome feedback: Stage 1: Technology feedback (medical and compliance alerts) notifies CP of discrepancy in patient's health result (knowledge of result) Stage 2: CP-based outcome feedback gives information to patient on their health result (knowledge of result) as well as how much (change) or how fast (velocity) their result has changed over time
Conditions for effectiveness	Feedback is provided repeatedly	Feedback to CPs and patients provided repeatedly
	Task is relatively simple or familiar	CP actions and patient adaptations are simple and sometimes familiar (e.g., elevate feet)
Consequences of feedback	Activates motivational processes to reduce discrepancy (expend effort to implement actions)	CP and patient are motivated to reduce discrepancies due to goal alignment
(2) Effects of Negative Feedback at the Lower (Task Detail) Regulation Level		
Feedback operating at this level	Process feedback (e.g., corrective)	Corrective feedback given to patient in stage 2
Conditions for effectiveness	Feedback is informational rather than controlling	Feedback given to patient is designed as informational
	Task is complex or new (feedback interferes with simple tasks if feed-back is immediate and overlaps with task)	Patient adaptations are relatively simple (but feedback is delayed and does not overlap or interfere with task)
Consequences of feedback	Activates learning processes to reduce discrepancies (generating and testing hypotheses)	Patient learns how to reduce discrepancies as feedback allows for testing and confirming hypotheses (e.g., try this and see if you feel better tomorrow)
(3) Effects of Negative Feedback at the Upper (Self-Related) Regulation Level		
Feedback operating at this level	Self-enhancing (e.g., constructive criticism) and self-threatening (e.g., normative feedback, blame) feedback	We conceptualize personal feedback (information that projects a sense of care, appears well-intentioned, is sensitive to emotional and cognitive needs, and shows a pathway to improvement)
Conditions for effectiveness	Feedback fosters confidence and self-efficacy	Personal feedback given to patient is considerate, non-threatening, and projects confidence and hope toward attaining the goals
	Task is important for self-goals	Adaptations are generally important for patient's quality of life
	Task is relatively simple or familiar	Patient adaptations are relatively simple and sometimes familiar
Consequences of feedback	Activates meta-task goals. If condi-ions are met, attention is redirected to the intermediate level to activate motivational processes in order to reduce discrepancies	Conditions are mostly met. Feedback redirects attention to motivational processes to reduce discrepancies

Appendix B

Construct Definitions and Operationalization

Construct Definition	Data Source	Operationalization	Measurement
Technology feedback: Information provided by a telemonitoring system regarding a patient's health-related results (vitals readings not taken or are discrepant from goal). We focus on two types of technology-based feedback that both direct attention at the intermediate level of the regulation hierarchy.		We focus on repeated exposure to feedback, which represents the extent to which CPs receive different types of alert information over a period of time.	
Medical alerts: Information on the results of a patient's vitals readings (knowledge of result feedback).	Secondary data generated automatically in the tele-monitoring system when patients use the devices	The information on a patient's vitals results is obtained via at-home devices that take daily readings of up to four vital signs relevant for patients with COPD and/or CHF: blood pressure (measured by blood pressure device), weight (measured by weight scale), oxygen saturation (measured by SpO2 pulse oximeter), and blood glucose (measured by gluco-manager). The alerts are automatically generated when there is a discrepancy between one or more of the readings and the thresholds established by the patient's physician. Alerts are logged in the system's task manager tool used by the provider (CP). The system records the date an alert was activated, the threshold that triggered the alert (e.g., SpO2 less than 88 % for 2 consecutive readings, weight increase of 1 Kg), and the actual reading (e.g., SpO2: 87, weight: 59.2 kg).	Count variable: number of daily alerts, aggregated over 1-week periods
Compliance alerts: Information on a patient's state of adherence to using the telemonitoring technology to take vitals readings (knowledge of result feedback).	Secondary data generated automatically in telemonitoring system when patients don't use the devices	The information on a patient's compliance is obtained via at-home devices that record every time a patient takes a reading using one of their assigned medical devices. The alerts are automatically generated when no readings have been recorded within a 24-hour period. Alerts are logged in the system's task manager tool used by the provider (CP).	Count variable: number of daily alerts, aggregated over 1-week periods
Provider feedback (CP feedback): Information provided by a care provider (CP) regarding a patient's health-related results. We focus on three types of feedback, each directing attention at a different level of the regulation hierarchy.		We focus on repeated exposure to feedback, which represents the extent to which patients receive different types of feedback over a period of time.	

Outcome feedback: Information about a patient's health-related result (knowledge of result) coupled with information on how much or how fast the result has changed over a given period of time. The feed-back can convey differences between the current result and a previous reference point (change in result), and/or convey the rate at which the current result has changed from a previous reference point (rate of change, or velocity). Outcome feedback directs attention at the intermediate (focal task) level and may activate motivational processes (Kluger and DeNisi 1996)	Content analysis data coded from the CP's qualitative notes	Outcome feedback was classified if the note reflected information related to the task (i.e., managing discrepancy in patient's condition). Outcome feedback provided information to help the patient understand past readings and behavior (how current readings compare to past trends) as opposed to correct their future behavior.	Count variable: number of outcome feedback items, aggregated over 1-week periods
Corrective feedback: Information on the process by which the present discrepant state or result has occurred and/or the means for reducing the discrepancy. The infor-mation contains cues that help patients to correct errors and to confirm hypotheses (or reject erroneous ones) about how to reduce the discrepancy. Corrective feedback directs attention at the lower (task detail) level and may activate learning processes (Kluger and DeNisi 1996).	Content analysis data coded from the CP's qualitative notes	Corrective feedback was classified if the note reflected information that provided patients with cues to correct the discrepancy in the patient's condition or to improve adherence to taking daily readings. The feedback highlighted problems related to how the patient was managing their condition and offered recommendations for correction (e.g., proper use of telemonitoring devices; behavioral modification regarding exer-cise or nutrition; medication manage-ment; proper use of telemonitoring devices).	Count variable: number of corrective feedback items, aggregated over 1-week periods
Personal feedback: Information that projects a sense of care, appears well-intentioned, is sensitive to the emotional and cognitive needs of the individual, and shows a pathway to improvement. Personal feedback directs attention at the upper (self-related) level and may activate motivational processes (Kluger and DeNisi 1996).	Content analysis data coded from the CP's qualitative notes	Personal feedback was classified if the note reflected the CP's concern about the personal day-to-day routine of the patient or the patient's mood or attitude. Feedback was non-threatening in that it encouraged general well-being (e.g., eating three meals a day) or validated patient frustrations (e.g., doctors are too busy) or beliefs (e.g., health providers care about patient well-being). Feedback also reassured patients that they were not doing anything wrong when they were feeling anxious or con-cerned about adhering to task goals related to their program.	Count variable: number of personal feedback items, aggregated over 1-week periods
Patient adaptation: Adjustments and change efforts dis-played by patients following the introduction of negative feedback. Adaptation efforts include behavioral elements such as changes to habits and the tasks or procedures imple-mented, as well as cognitive ele-ments such as changes to beliefs and knowledge (i.e., learning) (Barki et al. 2007; Beaudry and Pinsonneault 2005).	Content analysis data coded from the CP's qualitative notes	Patient adaptation was classified if the note reflected changes in self-management behaviors (e.g., administer oxygen, seek help from a doctor), as well as evidence of learning if the patient had taken appropriate action prior to the CP providing feedback. We focus on adaptations that are relatively quick to implement (e.g., going for a walk, breathing techniques, foot elevation)	Count variable: number of adapta-tions (i.e., self-manage, seeking help), aggregated over 1-week periods

Calls to 911: The likelihood of a patient to call an emergency ambulance to signal a health issue related to their chronic condition(s) that may require transport to a hospital or emergency room.	Secondary data from centralized 911 call and transport system	911 calls are coded by incident type (e.g., clinical exacerbation, falls, injury) and only 911 calls related to chronic disease exacerbations were included.	Binary variable: We used independent Bernoulli trials to model the likelihood of a patient calling 911 on a given week
Control variables Gender: Gender of patient [Binary variable (1= if male)] Age: Age of patient in years [Continuous variable] Geography: Geographic location where patient lives (urban vs. rural) [Binary variable (1 = if urban)] Comorbidities: Number of existing co-occurring chronic illnesses in addition to their primary condition diagnosed prior to program admission [Ordered categorical variable (0= no co-occurring conditions to 1= one co-occurring condition)] Emergency medical service (EMS), each in a geographic location and employing a number of CPs [Categorical variable (1 = EMS1 to 9 = EMS9)]			

Appendix C

Alerts and Notes Summary

	Compliance	Medical	Aggregate
Total Alerts	23,879	9,922	33,801
Non-Activated (No Feedback Provided)	21,352	3,178	24,530
Alerts Activated	2,527	6,744	9,271
% of Alerts Activated	11%	68%	27%
Activated Alerts Noted	2,502	5,463	7,965
% of Activated Alerts Noted	99%	81%	86%

Appendix D

Content Analysis Reliability Scores

	Frequency	Krippendorff's Alpha	Holsti's Intracoder Reliability
Outcome Feedback	874	0.931	0.992
Corrective Feedback	1,685	0.919	0.973
Personal Feedback	1,978	0.903	0.978
Patient Adaptation	463	0.970	0.984

Appendix E

Sample Alerts, Feedback and Adaptation (from Notes)

	Patient	Alert	Note Details
Outcome Feedback	165	Systolic greater than 180 mmHg and Diastolic greater than 110 mmHg: 239/136	Client states she is feeling anxious. Described her BP trend over the last few weeks and that is was much higher than normal.
	34	Systolic less than 90 mmHg: 79/57	Reviewed log of BP with patient for last 2 weeks and his low readings seemed to be related to humidity. He said he feels no worse than normal but the low readings made him nervous.
	44	SpO2 less than 88 % for 2 consecutive readings: 87%	Patient states they are doing fine, explained their average reading was 91% and seemed to be on a downward trend.
	113	Weight increase of 1 kgs - Weight: 109.0 kgs	Called to inform patient his weight was up a bit and he said he had not been sleeping well again. A little more short of breath than normal.
Corrective Feedback	157	SpO2 less than 88 % for 2 consecutive readings: SpO2 85%	Saw client today told her to make sure she uses Sp02 every time she exerts herself and that would make a difference.
	54	Heart Rate less than 50 bpm: HR 42	Patient has poor circulation and showed him some exercises to increase circulation and encouraged him to do them every morning.
	174	Heart Rate greater than 110 bpm: Heart Rate: 120	Patient not taking digoxin as it makes her very tired and she is also not taking her 40 mg lasix, because of the diuretic effect. If unable to cope with side effects, ask for another medication. Try taking 0.5 lasix pill until she speaks with doctor.
	118	Weight increase of 2 kgs over 2 days: 155.2 kgs	Pt has been eating high sodium meals for past few days. Encouraged to avoid.
Personal Feedback	126	Heart Rate greater than 110 bpm for 2 consecutive readings: HR 126	Checked with patient, stating he was feeling "anxious" as he was having some personal issues. Refusing appointment today (going to church) but has appointment to see doctor tomorrow.
	133	Systolic greater than 180 mmHg: BP: 197/103	Patient feeling unwell today. Tired. I expressed concern [for her] and that she was only eating one meal per day and inquired about why she was not taking pain relief.
	124	Compliance – no readings taken in 24 hours	Patient feeling of no energy and apologized for not taking reading. She says 'she forgets'. Told her to not feel bad, it was ok but explained that readings help monitor how she was doing.
	194	Heart Rate less than 50 bpm: HR 41. SpO2 less than 88 %: Sp02 84%	No complaints. Feeling ok. Concerned about her heart rate and SpO2 readings and wonders if she is doing something wrong. Reassured client that I was watching her closely and she was doing nothing wrong.
Patient Adaptation	157	Patient visited doctor as advised and was prescribed a water pill and is feeling much better. Denies any shortness of breath.	
	34	Checked back with patient about low BP readings. He said he just took it easy and stayed out of the heat. Patient feeling well with no shortness of breath.	
	74	Client following techniques I prescribed to calm himself down and is taking his BP while he feels anxious to calm himself.	
	113	Patient increased his water pill and cut out the hot dogs....he feels better today.	

Appendix F

Indirect Effects of Alerts on Patient Adaptation

Coefficient		Std. Error	Z	p	LCL	UCL
MedAlerts ➔ FeedOut ➔ PatAdapt	0.029***	0.004	6.51	< 0.0001	0.020	0.038
MedAlerts ➔ FeedCorr ➔ PatAdapt	0.016***	0.003	5.86	< 0.0001	0.011	0.022
MedAlerts ➔ FeedPers ➔ PatAdapt	0.020***	0.003	7.59	< 0.0001	0.015	0.025
CompAlerts ➔ FeedCorr ➔ PatAdapt	0.017***	0.005	3.19	0.001	0.007	0.028
CompAlerts ➔ FeedPers ➔ PatAdapt	0.019***	0.006	3.24	0.001	0.007	0.030

*p < 0.05; **p < 0.01; ***p < 0.001