Person-Centered, Technology Enhanced Care Model

For Managing Chronic Conditions: Development and Implementation

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Abstract

Background:
Caring for individuals with chronic conditions is labor intensive, requiring ongoing appointments, treatments, and support. The growing number of individuals with chronic conditions makes this current support model unsustainably burdensome on health care systems globally. Mobile health (mHealth) technologies are increasingly being used throughout health care to facilitate communication, track disease, and provide educational support to patients. Such technologies show promise, yet they are not being utilized to their full extent within US health care systems.

Objective:
The purpose of this study was to examine the utilization of staff and costs of a remote monitoring care model in persons with and without a chronic condition.

Methods:
At Dartmouth-Hitchcock Health, 2,894 employees volunteered to monitor their health, transmit data for analysis, and communicate digitally with a care team. Volunteers received Bluetooth-connected consumer-grade devices that were paired to a smartphone application that facilitated digital communication with nursing and health behavior change staff. Health data were collected, automatically analyzed, and generated behavioral support communications based on those analyses. Care support staff were automatically alerted according to purpose-developed algorithms. In a subgroup of participants and matched controls, we used difference-in-difference techniques to examine changes in per-capita expenditures.
Results:
Participants averaged 41 years of age; 72.70% (n = 2,104) were female and 12.99% (n = 376) had at least one chronic condition. On average, each month, participants submitted 23 vital sign measurements, engaged in 1.96 conversations, and received 0.25 automated messages. Persons with chronic conditions accounted for 40% of all staff conversations, with higher per-capita conversation rates for all shifts compared to those without chronic conditions (P<.001). Additionally, persons with chronic conditions engaged nursing staff more than those without chronic conditions (1.40 & 0.19 per-capita conversations, respectively, P<.001). When compared to the same period in the prior year, per-capita healthcare expenditures for persons with chronic conditions dropped by 15% (P=.06) more than did those for matched controls.

Conclusions:
The technology-based chronic condition management care model was frequently used and demonstrated potential for cost savings among participants with chronic conditions. While further studies are necessary, this model appears to be a promising solution to efficiently provide patients with personalized care, when and where they need it.

Keywords:
mHealth; mobile health; telemedicine; digital biomarker; person centered care; chronic condition; chronic disease
Introduction

US healthcare costs continue to rise, driven in large part by increasing prevalence of chronic conditions and longevity of those afflicted with them.[1] Chronic conditions can be broadly defined as a reduction in health that is not transmittable, which generally progress slowly, lasting for an extended period of time.[2, 3] Due to these factors managing chronic conditions is a large burden.[4] With health care spending approaching 20% of GDP and 20-40% of healthcare resources considered wasteful,[5-7] reducing the cost of managing chronic conditions is paramount. Some overuse of healthcare services is attributable to fee-for-service payment systems that require face-to-face encounters for reimbursement.[8, 9] While alternative payment models have been designed to mitigate waste[10] by engaging health care providers and their patients in self-care disease management,[10] those models still tend to rely on face-to-face visits and irregular and infrequent measurement to manage chronic conditions.

Among those with chronic conditions, reliance on face-to-face visits may delay interventions to mitigate health deterioration until symptoms are acute, thereby accelerating demand for expensive healthcare services such as hospitalizations, emergency room visits, and unplanned readmissions.[11] This is particularly true for persons with behavioral health issues, where early interventions can reduce the need for acute care.[12] Seemingly, redesign of chronic care management to engage patients in self-care, monitoring for early signs of deteriorating health, intervene early, and avoid unnecessary care would create value by improving health outcomes and reducing care costs.

Because behavioral and social factors are implicated in over ½ of premature deaths,[13-15] addressing these factors are critical to improving care value. Behavioral change
interventions can successfully address those factors;[16] however, because behavioral change is
difficult to induce and maintain,[12, 17] ongoing respectful patient engagement is essential.[18]
Technologically enabled real-time information exchange resulting in ‘just in time’ interventions
can increase patients’ feelings of autonomy,[19, 20] build competence in self-management of
chronic diseases,[20] and help patients manage their chronic diseases.[19, 21] Technology-
based solutions like mHealth (health care that utilizes mobile phones and other mobile devices)
have been shown to impact health related behaviors.[22]

Current technology allows for both active and passive collection of digital biomarkers,
their subsequent aggregation, analysis, and immediate feedback of information.[20, 23-25]
With decreasing costs of devices and cloud computing,[26] increasing smart phone penetration,
[27] and advancements in deep learning, mobile health applications are increasingly being used.
[28] While some of these applications have the potential to relieve some of need for face-to-
face encounters, they tend to focus on a specific disease (or body organ), typically do not
interact with patients’ healthcare teams, and do not always enhance patients’ understanding of
their health situation. A single application that is integrated with the patient medical record and
is supported by backend analytics could reduce the burden of interacting with technology while
aggregating holistic ‘in-vivo’ data into actionable information for the patient, care team, and
health system.

Implementation of mHealth interventions has been studied in a variety of settings and
across many disease states.[29] Most studies have examined the disease-specific impact that
mHelath applications (developed by academic groups and not designed for widespread use by
consumers) have over a short time period within small sample populations.[29, 30] To date,
mHealth interventions have neither been integrated within a health system nor have allowed for comparison of users with chronic disease states to healthy patients.[30] Further, studies have not examined how support staff are used - a critical aspect of mHealth implementation as payers and care delivery system leaders need to consider workforce impact before they fund such efforts.[30] To address these gaps in the literature, we examined an mHealth application and remote care system designed for broad consumer use, determined how and when staff were used to support the system, and calculated the cost impact of the application on individuals with and without chronic conditions.

In the spring of 2016, Dartmouth-Hitchcock Health (DHH) – an integrated healthcare system headquartered in Lebanon, NH – developed a technology- and sensor-based management/health care model called ImagineCare. The model was piloted with volunteer employees who were enrolled in its self-insurance product. We sought to determine ImagineCare's use by – and healthcare spending impact on – two groups within DHH’s employee population: persons with and without chronic conditions.
Methods

A multi-disciplinary team including nurses, physicians, designers, IT developers, hospitality specialists, and researchers developed a new care model, following an established methodology of disruptive innovation.[31] Over three years, the team explored aspects of managing chronic conditions: current care delivery models from the patient and provider perspective, evidence-based guidelines, and behavioral change methods. Devices and software were assessed and selected based on ease of use, technical integration possibilities, cost effectiveness, and clinical relevance.

The final ImagineCare delivery model was based on remote monitoring, digital communication, cloud-based analytics, and personal behavioral change support. The model consisted of 1) a 24/7 care support center with staff trained in behavioral change, 2) a clinical workflow application, 3) a mobile application with companioning Bluetooth-enabled devices for the participants, and 4) a cloud-based data processing solution (Figure 1).

Figure 1: Architecture of ImagineCare care model.
The care support center consisted of a clinical care team available 24/7 to the participant through text or voice-based communication. The team was staffed by licensed nurses and health navigators (non-medical staff, trained in customer service and basic health services). Both groups were specifically trained in behavioral change and remote support of patients; they were also coached to provide high quality customer service designed to keep participants engaged with their health and well-being. The staff responded both to incoming calls or messages from participants and to alerts that were triggered by collected data. Health navigators passed conversations on to nursing staff based on triage guidelines, clinical judgement, or at the participant’s request. Navigators reached out to participants when cloud-
based algorithms identified declining engagement, out-of-normal range monitored vital signs, or negatively trending vital signs.

The iOS-developed application had three core functional areas: health data, personal profile, and secure messaging. Health data were collected through sensors, by manual entry, or by participant response to questions. The personal profile section provided valuable context to clinicians by documenting health goals, personal preferences, and social data. The secure messaging function allowed participants to connect to the care team when it suited them best.

To complement personal messages sent by the clinical care team, the system automatically communicated clinical information and suggestions, nudges, and support throughout the application. All system generated messages used variations on language and collated participant-specific information to make the communication feel personalized. Colors and language were deliberately chosen to support positive behavior change and enjoyment and to reduce stress and anxiety. The application itself had either password or biometric security, depending on the participant’s preference.

The system collected data through passive or active encounters with participants, stored data in a cloud-based database, and automatically analyzed them according to medical-condition specific care pathway algorithms. Condition specific care pathways had been developed through adaptation of systematic reviews of clinical evidence to the patient population via team clinician consensus and by tailoring pathways to enhance self-care opportunities. Safety was held paramount as no logic made a diagnosis and all decision points were examined by a nurse or health navigator for a final intervention recommendation. All cloud processes and information were stored on HIPPA compliant data services. All algorithms
were tested by the developers to ensure patient safety. The application and databases were subject to rounds of vulnerability testing by a third party, ensuring that personal participants’ information was secure.

Device connectivity, application functionality, and message communication were tested over a two-month period by 50 healthy individuals. Each device was tested for its ability to connect to the application, collect data, engage algorithms, and respond to both the application and the clinical care team. The testing confirmed that the patient and clinician experience were good, found that data collection and algorithm execution were accurate, and verified that no patient safety issues arose.

Voluntary enrollment in ImagineCare began in March 2016 and ImagineCare was launched in May 2016. Volunteers were solicited through emails directed at employees who were insured by DHH’s self-insurance product; 2,849 volunteers enrolled, which entailed creating a secure personal account verifying basic information, downloading the mobile application, receiving Bluetooth enabled sensory devices by mail, and connecting those devices to the mobile application.

The devices that were sent were dependent on the participants needed support. For those without a chronic condition a fitness tracker smart watch was sent to support general healthy living and wellness which included collecting data and providing feedback on sleep, physical activity, and mental health. In addition to this support those with chronic conditions received care and collected data specific to their conditions, for example, blood pressure was measured for those with hypertension, weight was measured for those with congestive heart failure, and blood glucose was measured for those with diabetes.
Use Of The ImagineCare System

To analyze the use of the application for chronic disease management, we classified volunteers into two mutually exclusive groups: persons with or without chronic conditions. Persons with chronic conditions were defined by documentation of ICD-9 codes indicating diabetes, hypertension, congestive heart failure, and/or chronic obstructive pulmonary disease in the prior year. Persons without these codes were defined as without chronic condition. After comparing demographics for these two groups of participants (including a US Census Bureau estimate of the mean family income of each volunteer’s ZIP Code of residence), we evaluated how they used the ImagineCare system in three ways. First, we examined their enrollment, over time, and the number of days it took each participant to complete enrollment. Second, we examined how often participants uploaded vital sign data (data collected from any of the peripheral devices that were connected to the app). Third, we evaluated the frequency and timing of ‘conversations’ that each group had with the system. A ‘conversation’ was defined as a conglomeration of texts and/or phone calls having to do with a particular event; the date and time of the conversation was that of the first interaction regarding the event – whether it was precipitated by participant, staff, or system logic. The ‘purpose’ of the conversation was recorded by the ImagineCare nurse or health navigator that communicated with the participant at the time of completion of the communication.
Impact On Care Costs

Finally, for a subset of 1,235 volunteers who had been employees for the prior year and remained in the program throughout the entire pilot period, we assessed total allowed healthcare charges that the participant incurred, partitioned into three types of care: hospital, emergency room (ER), and outpatient care (including medications). To make this comparison robust, we used age, sex, hierarchical condition category (HCC) score, and chronic condition status to match volunteers to non-participating employee controls, using a 3:5 ratio. We conducted a difference-in-difference analysis that compared the intervention period to baseline charges incurred during the same 9-month period in the prior year for participants and controls, for both with and without chronic condition groups.

We used R version 3.4.1 to conduct all analyses. We used Student's t-tests to compare continuous variables and the chi-square test to compare categorical variables; all significance tests used 2-tailed alpha = .05. As charge data were highly skewed and kurtotic, we log-transformed them to conduct statistical analyses, although for ease of interpretation, we also report non-transformed results. The study was found not to be Human Subjects Research by Dartmouth College’s Committee for the Protection of Human Subjects.

Results

Use Of The ImagineCare System

Of the 2,894 participants in the pilot project, 2,518 were considered without chronic condition and 376 were considered to have a chronic condition; participants without a chronic
condition were younger and more likely to be female than persons with chronic conditions (Table 1). The two cohorts took a similar amount of time to enroll in the program after having been emailed an invitation to do so and had similar estimated annual incomes.

Table 1. Characteristics of participants with and without a chronic condition in the ImagineCare pilot. Student’s t-test and chi-square tests were performed on continuous and categorical variables, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Chronic Condition</th>
<th>Without Chronic Condition</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>376</td>
<td>2518</td>
<td></td>
</tr>
<tr>
<td>Mean age in years (SD)</td>
<td>52.0 (11.7%)</td>
<td>39.3 (12.2%)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Sex (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>215 (57.2%)</td>
<td>1889 (75.0%)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Male</td>
<td>235 (47.2%)</td>
<td>625 (24.8%)</td>
<td></td>
</tr>
<tr>
<td>Other/Unknown</td>
<td>6 (1.6%)</td>
<td>4 (0.2%)</td>
<td></td>
</tr>
<tr>
<td>Mean days to complete enrollment (SD)</td>
<td>12.0 (33.3)</td>
<td>10.4 (23.6)</td>
<td>.24</td>
</tr>
<tr>
<td>Estimated ZIP Code level income in $ (SD)</td>
<td>67,500 (21,400)</td>
<td>66,200 (19,700)</td>
<td>.25</td>
</tr>
</tbody>
</table>

Cumulative enrollment of participants with and without a chronic condition was similar, over time (Figure 2). Enrollment was fastest between March and May and slowed somewhat between May and September when it essentially stopped. The proportion of participants who submitted at least one vital sign each month consistently fell for both persons with and without a chronic condition during the pilot, dropping to less than 10% of persons without a chronic condition by the end of the pilot period; persons with chronic conditions remained somewhat more engaged with the system throughout the pilot period, though that engagement waned.
The per-capita number of vital signs submitted by engaged patients remained stable for the cohort without a chronic condition but increased somewhat among persons with chronic conditions between May and October, before stabilizing (Figure 3B). Although they comprised only 13% of the population, persons with chronic conditions contributed over 28% of all submitted vital signs.

**Figure 2.** Cumulative enrollment in the pilot program for participants without chronic condition (dotted line) and chronic condition participants (solid line), March 2016 – January 2017.

**Figure 3.** For without chronic condition (dotted lines) and chronic condition (solid lines) cohorts for each month of the pilot: A. The percent of enrollees who submitted at least 1 vital sign and
B. The average number of vital signs submitted (for individuals who submitted at least 1 vital sign that month).

A. 

B. 

Persons with chronic conditions also accounted for 40% of all staff conversations, with higher per-capita conversation rates for all shifts \((P<.001\text{ for all, Table } 2)\). For both with and
without chronic condition cohorts, participants engaged in conversations significantly more frequently over in later hours - toward the 16:00-24:00 shift (Table 2). Administrative conversations accounted for over 75% of conversations between persons without chronic conditions and with staff; administrative conversations and clinical alerts each accounted for around 40% of conversations that persons with chronic conditions had with staff. Conversations were most common with health navigators (76%), however, persons with chronic conditions were much more commonly referred to nursing staff (42% vs. 12% for without chronic condition participants, \( P < .001 \)). About 70% of all nursing staff conversations were with the chronic condition group, as compared to 30% of health navigator staff conversations.

Table 2. Number of total conversations and conversations per patient between staff and participants with and without chronic condition by shift, purpose, and staff roll. Chronic condition participants had statistically significantly more conversations per-capita in all shifts (\( P < .001 \) for all), and both cohorts engaged in statistically significantly more conversations during the 16:00-24:00 shift (Chronic: compared to 00:00-08:00 \( [P < .001] \) or 08:00-16:00 \( [P < .001] \), Without Chronic: compared to 00:00-08:00 \( [P < .001] \) or 08:00-16:00 \( [P = .006] \)). The purpose of conversations was distributed similarly in with and without chronic condition cohorts except in the case of clinical alerts (\( P = .01 \)). Both groups had significantly more per-capita conversations with Health Navigators than Nurses (Chronic: \( P < .001 \), Without Chronic: \( P = .003 \)), and chronic condition participants had significantly more per-capita conversations with both staff types than participants without chronic condition (Health Navigators: \( P < .001 \), Nurses: \( P < .001 \)).
Patterns of communication across time of day and day of week differed somewhat when comparing with and without chronic condition cohorts. Both groups had their highest concentration of conversations after noon, regardless of day (Figure 4); however, when compared to the without chronic condition group, persons with chronic conditions had relatively more conversations in the late night, and Mondays appeared to be the day on which participants without a chronic condition most frequently communicated with the system.

Relatively high concentrations of communications with nurses were more sporadic than those with health navigators throughout the week; however, as the week progressed health navigators and nurses had similar concentrations of conversations (Figure 5).
**Figure 4.** Time of communications by day, hour, and cohort, for March 2016 – January 2017.

Each week is separated by hours scored by percentile of conversations for that hour. The percentile of conversations (0 corresponding with 0 conversations for that hour) for persons with chronic conditions (With CC) and without chronic conditions (Without CC) are plotted for each hour in each day. The largest concentration of conversations for participants without chronic condition was on Mondays between 14:00-15:00, while it was on Sundays between 15:00-16:00 for persons with chronic conditions.

**Figure 5.** Time of communications by day, shift, and staff role, for March 2016 – January 2017.

Each week is separated by hours scored by percentile of conversations for that hour. The percentile of conversations (0 – corresponding with 0 conversations for that hour) for health navigators and nurses are plotted for each hour in each day. The largest concentration of
conversations with health navigators was Mondays between 14:00-15:00; with nurses, it was Sundays between 15:00 - 16:00.

There were no reports of adverse health events. System bugs were limited to incorrect responses to question scores, which were investigated and fixed.

**Impact On Care Costs**

Our sub-analysis that used matched controls to conduct a difference-in-difference analysis of the cost-impact of the new care model found that the variables used for matching were similar for participants and controls for with and without chronic condition cohorts with the exception of prior period ER charges, that were higher for participants without a chronic
condition than for matched controls \((P=.01)\) (Table 3). Our difference-in-difference analysis found that program participation was associated with trends toward lowered ER charges for the without a chronic condition cohort (29% reduction, \(P=.08\) and lowered outpatient (20% reduction, \(P=.052\) and total charges (16% reduction, \(P=.055\) for the cohort with chronic conditions (Table 4).

Table 3. Comparison of the characteristics and pre- and post-intervention charges for program participants and matched controls in the with and without chronic condition cohorts (actual mean values are provided, but \(P\) values for charge data are based on results using log-transformed data). Bold text indicates \(P<.05\); italic text indicates \(P<.10\).

<table>
<thead>
<tr>
<th></th>
<th>Chronic Condition</th>
<th></th>
<th>Without Chronic Condition</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Program participants</td>
<td>Matched controls</td>
<td>(P) value</td>
<td>Program participants</td>
</tr>
<tr>
<td>N</td>
<td>193</td>
<td>343</td>
<td></td>
<td>1042</td>
</tr>
<tr>
<td>Age in years</td>
<td>51.1</td>
<td>51.9</td>
<td>.37</td>
<td>39.7</td>
</tr>
<tr>
<td>% Male</td>
<td>36.3</td>
<td>36.4</td>
<td>.97</td>
<td>26.3</td>
</tr>
<tr>
<td>Hierarchical Condition Category (HCC) score</td>
<td>4.13</td>
<td>4.60</td>
<td>.16</td>
<td>1.77</td>
</tr>
<tr>
<td>Prior period</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acute care charges ($)</td>
<td>1545</td>
<td>1674</td>
<td>.74</td>
<td>274</td>
</tr>
<tr>
<td>ER care charges ($)</td>
<td>296</td>
<td>356</td>
<td>.17</td>
<td>\textbf{191}</td>
</tr>
<tr>
<td>Outpatient charges ($)</td>
<td>8456</td>
<td>7533</td>
<td>.07</td>
<td>3970</td>
</tr>
<tr>
<td>Total charges ($)</td>
<td>10297</td>
<td>9563</td>
<td>.09</td>
<td>4435</td>
</tr>
<tr>
<td>Intervention period</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acute care charges ($)</td>
<td>1305</td>
<td>1178</td>
<td>.73</td>
<td>317</td>
</tr>
<tr>
<td>ER care charges ($)</td>
<td>252</td>
<td>479</td>
<td>.06</td>
<td>192</td>
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<tr>
<td>Outpatient charges ($)</td>
<td>8402</td>
<td>9159</td>
<td>.59</td>
<td>5201</td>
</tr>
<tr>
<td>Total charges ($)</td>
<td>9959</td>
<td>10816</td>
<td>.53</td>
<td>5710</td>
</tr>
</tbody>
</table>
Table 4. Results of the difference-in-difference charge analysis for with and without chronic condition cohorts, showing only the difference-in-difference statistic. The regression included the following variables: age, sex, Hierarchical Condition Category (HCC) score, time, case, and time*case (which represents the difference-in-difference statistic, after adjusting for the other variables). Where $P<.10$ for the natural log of the charge categories, 95% confidence intervals (CIs), and the $P$ value and coefficient ($\beta$) for non-log-transformed charges are provided; if $P\geq.10$, cells are left blank. Neither the with nor the without chronic condition cohort had difference-in-difference statistics that were $P<.10$ for Acute care.

<table>
<thead>
<tr>
<th>Type of charge</th>
<th>Chronic Condition</th>
<th>Without Chronic Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$ LN charge</td>
<td>95% CI</td>
</tr>
<tr>
<td>Acute care</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ER care</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outpatient</td>
<td>-0.43</td>
<td>-0.868 – 0.004</td>
</tr>
<tr>
<td>Total</td>
<td>-0.44</td>
<td>-0.884 – 0.009</td>
</tr>
</tbody>
</table>

Discussion

Within its self-insured employee population, Dartmouth-Hitchcock Health designed, piloted, implemented, and studied a remote monitoring system designed to improve patients’ self-management of their health status, particularly for persons with chronic conditions. We found that persons with or without chronic conditions signed up for the volunteer program similarly; however, those with chronic conditions were older and more likely to be male.
Persons with chronic conditions used ImagineCare differently than did participants without a chronic condition: though both groups used the system less as time progressed, persons with chronic conditions appeared to be actively engaged with the system for a longer time period. Engagement fell considerably in both groups over the pilot period at similar rates. Interestingly, even at the beginning of the pilot, only about ½ of the participants in either cohort were actively engaged with the system. Finally, among persons with chronic conditions, our difference-in-difference analysis uncovered a substantial potential for reductions in care costs when compared to matched controls, while the participants without chronic conditions did not demonstrate such large charge reductions.

Our results suggest that effort needs to be expended to engage patients in the use of mHealth applications. While the engagement we experienced was higher than that found in a Federally Qualified Health Plan,[34] several approaches might improve system engagement going forward. First, evaluation of participants' 'eHealth literacy' – the ability patients to communicate through written text, a working knowledge of computers or smart phones, and a basic understanding of their health and treatment[35, 36] – might have helped to target participants who lacked such understanding or demonstrate to them that use of the system might have been beneficial.[37] While the observed higher engagement might have resulted from the testing process and user-centered design, the engagement might have been improved by ensuring that there was a good ‘fit’ between the application, the end-users, the recruitment approach, and the treatment process.[34] Nonetheless, the relatively low engagement suggests that more should be done to encourage customers of such systems to use technology to monitor and manage their health.
Our results suggest that care models like ImagineCare can be integrated into traditional healthcare delivery systems, but that a focus on enrolling patients with chronic conditions would be wisest: they are more likely to remain engaged and have the greatest potential to generate cost savings. While the pilot effort was successful, there were substantial technical challenges in managing and coordinating data input from a multiplicity of systems, which as others have noted, highlights the lack of standards for technology inter-operability in implementing mHealth programs. Not only were data collection and storage difficult because of the need to integrate firmware, schema, and data types, but also ongoing data analytics overwhelmed the initial computational power provided to run the system. Much of the system’s success relied on difficult integration of devices that traditionally run on third-party applications; this creates an opportunity for device manufacturers to produce devices with open software development kits. Should healthcare organizations want to develop similar care models, they should use existing technologies and leverage existing capacity for large data management and analysis.

Appropriate technical and clinical staffing levels are also necessary to effectively and efficiently run such systems; staffing levels must be adapted to meet the needs of particular patient populations, by shift, day, and time since enrollment. Given the high variability in the type and time of communications, the timing of communications during a week, and the decline in communications over time, flexible scheduling based on system engagement may be most efficient. Our results indicate that systems managing a higher proportion of persons with chronic conditions might require more nursing staff, particularly in later shifts and later in the week.
The use of remotely collected data which monitors health and behavior is an emerging area of research.[41] Such data could be considered 'digital biomarkers'[42] – objective information that can be used to predict changes in health status. It is difficult, costly, and time consuming to collect, process, and analyze non-digital predictors,[43, 44] and the use of digital biomarkers offers a more efficient method of identifying such markers as the use of devices continuously collecting data increases. One critical requirement in the development of digital biomarkers is connecting these novel measurements to health outcomes.[42] In the context of accelerating US healthcare spending,[45] and private endeavors to address spending growth,[46] care models that can use digital biomarkers might have market advantages.

The potential cost savings due to a remote monitoring care system could be highly dependent on the payment model of the implementing health system. Fee-for-service models may have the least to gain as the goal of remote monitoring care is to reduce the utilization of standard face-to-face services through prevention and point of need interventions. Payment models such as Accountable Care Organizations (ACOs), value-based models, or those that use bundled payment structures might have much greater savings.

**Limitations**

Our analysis has several limitations. First, ours was an open study and our cost comparison used retrospectively matched controls. To better evaluate the impact of such systems on the health of the population and care costs, future studies should prospectively identify control groups and concurrently collect data from them. Second, our definition of having a chronic condition was limited. We believe that this potential bias was minimal as
Hierarchical Condition Category (HCC) scores between the cohorts were meaningfully different, and we observed differences in utilization. If such a threat to internal validity was large observed differences would be biased to the null. Third, more in-depth analyses of how patients used the system would be valuable. For instance, analysis of time spent interacting with the system, responses to system-generated automated messages, eHealth literacy, and measures of patient engagement would be valuable. Fourth, we did not evaluate the impact of the system on clinicians within the healthcare delivery system: analysis of their ability to integrate data obtained from such programs into their clinical decision-making processes and patient encounters would be valuable. Additionally, here, we only examine the use of the monitoring model and not the health status of participants measured by it. Finally, we analyzed the implementation of a single monitoring model in a single organization for a relatively brief time period; longer studies across multiple systems would be informative and might generate different results.

Conclusions

Our results suggest that persons with and without chronic conditions used a remote monitoring care model differently and that their needs for support within such systems differed. This new care delivery model showed promising results, but the long-term success will depend on sustainably engaging patients to participate in the system, developing triage structures that meet patient and health system needs, and appropriately staffing the system so patients get the care that they want and need, nothing more and nothing less.
Acknowledgements:

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Conflict of Interest:

Dr. Weinstein and Mr. Petersen helped develop and implement the ImagineCare healthcare management product evaluated herein at Dartmouth-Hitchcock. Dr. Norin is a minority owner of Lifecarex Sweden, the distributor of the ImagineCare product. Dr. Weinstein serves on its board and has stock options.

Abbreviations:

Emergency Room (ER); Dartmouth-Hitchcock Health (DHH); Accountable Care Organizations (ACO); Hierarchical Condition Category (HCC); With Chronic Conditions (With CC); Without Chronic Conditions (Without CC); Natural Log (LN)
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