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Enhancing healthcare professional and caregiving staff informedness with data analytics for chronic disease management

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Abstract

An important area in healthcare to which data analytics can be applied is chronic disease management. The chronic care model is mostly patient-centric, so patients have been considered as the end users of data analytics. The information needs of healthcare providers have been overlooked. Drawing upon the theory of informedness and the transtheoretical model of health behavior change, we use a multicase study approach to investigate the information needs of different caregiving stakeholders in the spectrum of chronic diseases, and how data analytics can be designed to meet the varying needs of professionals and staff to support their informedness.

Keywords

Behavioral change, Chronic disease management, Data analytics, Healthcare informedness, Healthcare organizations, Physicians, Theory of informedness, Transtheoretical model

1. Introduction

A growing proportion of the world's population suffers from chronic illness today, and the economic burden of caring for such patients has become increasingly high. Nearly half of the U.S. population, for example, lives with a chronic condition, such as high blood pressure, diabetes, or asthma, and chronic diseases account for 70% of deaths [1]. Many such diseases are lifelong conditions which reduce patients' quality of life and stress their family members and caregivers. The goal of chronic disease management is to maintain a patient's health status by changing their living style, so patients can live as other people do.

Providing chronic disease care requires a long-term commitment from patients, healthcare professionals and caregiving staff [2]. The term, healthcare professional, refers to a physician, nurse, or other person who is qualified by education, training, licensure/regulation and facility privileging to perform a professional service within their scope of practice, and who must independently report the services provided [3]. Caregiving staff are people working in a volunteer-based community healthcare organization to assist residents to improve their health and well-being.

Many information systems (IS) have been developed to empower patients to manage their chronic disease, including monitoring vital signs, and providing feedback to encourage a healthier lifestyle. With the availability of an unprecedented volume, velocity and variety of primary data for individual patients, advanced analytical support typically is built into the systems [4] to further empower patients. Additionally, such tools help healthcare professionals and other caregiving staff to acquire relevant information, in order to make timely and evidence-based decisions and deliver more effective and personalized treatment, while reducing the costs of patient care. However, the explosion of data and information can cause problems due to information overload and difficulties with coordinating information to ensure all caregiving stakeholders are effectively informed.

According to the theory of informedness, informed users make better decisions to support the actions, choices, and outcomes they have available in a decision setting [5]. This enhances the value of their involvement in creating benefits. In the case of chronic disease management, healthcare informedness refers to the state and quality of information provided to stakeholders (patients, healthcare professionals and caregiving staff) to enable their decision-making and empower their desired actions.

We will focus on healthcare professional and caregiving staff, and first ask:

• How do healthcare professionals and caregiving staff differ in their needs for informedness in their roles, and in the different stages of the chronic *disease management process related to their patients' behavioral changes over time?*

Related to this question – and what remains unknown – is how data and data analytics can best support healthcare professionals' and caregiving staff's needs for healthcare informedness. Given the different roles played by healthcare professionals and caregiving staff during their patients' disease management process, we wish to find out how their needs for informedness differ. We also ask:

- *How can data analytics support the need for informedness of healthcare professionals and caregiving staff, and enable their desired actions to improve the health and well-being of patients with chronic disease?*

We will argue in this research article that the need for healthcare professional and caregiving staff informedness differs according to the roles each plays in the different stages of a patient's illness. Typically, healthcare professionals take responsibility for making key treatment decisions, while caregiving staff are responsible for monitoring patients regularly, and referring them to healthcare professionals when necessary. We will analyze the extent of informedness of these two stakeholders from a process-based view, using the *transtheoretical model of health behavior change*, a stage-based treatment model proposed by Prochaska and Velicer [6]. This describes a continuum of behavioral changes used to assess a patient's readiness in advance demonstrating new behavior (compliance with taking medication, getting appropriate exercise, following a proper diet, etc.). It also describes actions of healthcare providers at different stages that can encourage patients to change behavior. With differences in the informedness needs identified, we will then investigate how data analytics can support informedness, and thereby enhance desired actions.

We investigated the research questions using a multiple case-study method. This study advances our understanding of the use of data analytics to support the needs for informedness of healthcare professionals and caregiving staff caring for chronic disease patients. Our study contributes to the development of the theory of informedness in the healthcare context, by showing how data analytics can assist health professionals and caregiving staff. We also contribute to the design of the appropriate analytical components for managerial use in healthcare.

2. Theoretical background and literature review

2.1. Data Analytics in Healthcare

As healthcare becomes increasingly digitized, a variety of information on a patient can be collected through different sources, much the same as we have seen with product consumers, financial investors, residential energy and water users, commuters, and TV viewers [7,8]. In healthcare, data analytics have been used to predict which characteristics of people are associated with noncompliance with healthcare treatment procedures, allowing for more personalized interventions. Advances with Internet-of-Things (IoT) technologies, for example, support data capture of growing volume, variety, and immediacy, making it possible to construct detailed personal health value assessments, and gauging medical health and fitness levels through wearable devices. For example, RxAnte (www.rxante. com), a healthcare predictive analytics and decision support company, has developed methods to forecast medication adherence for specific therapies over different time frames, with more than 400 variables [9]. With this kind of information, a practice team can be given a target list indicating which patients should receive each intervention, to optimize the efficacy of outreach.

Patients' daily activities and changes in vital signs produce a large pool of data that suggests their lifestyle and health status. Practice teams can leverage tracking tools – wearable devices, mobile apps, medical devices and other remote monitoring systems – to capture and process digital trace data to provide such information. The most common application is remote monitoring to produce indicators of a patient's health [10]. Trend analysis of physiological parameters also can enable early detection of deterioration [11], and prompt early intervention by identifying anomalies.

Further, contextualized information and preventive suggestions can be made available to patients by associating their personal data with their locations, health indicators, weather conditions, and so on. Analytics based on mobile data can help determine opportune moments to deliver reminders to step up patient compliance [12], provide early warnings of abnormalities, and allow for faster treatment. Such information will also support lifestyle changes and enhance medication compliance. For example, a diabetic patient will be able to see the increase in her blood glucose level after a meal, and take action if it does not return to a normal baseline level by two hours later. Data analytics can also leverage association rules so the number of daily tasks a patient is required to perform can be monitored to establish a minimum support threshold [13].

2.2. Chronic disease management: stakeholders

Chronic disease management refers to "an organized, proactive, multi-component, patient-centered approach to healthcare delivery that involves all members of a defined population who have a specific disease … or a sub-population with specific risk factors" [14, p. 480]. (For other definitions of key terms in this article, see Appendix 1.) Some studies have shown that patients with chronic illnesses often receive less-than-optimal care [15,16]. One reason is that methods of the acute health delivery system are unsuitable for addressing some patients' needs, although these have emerged as a primary strategy for healthcare. The emphasis of chronic disease management has also shifted over the years to a more patient-centric rather than a physician-driven one. However, chronic disease management is a complex system approach that should coordinate the interaction among different stakeholders [17], such as patients, physicians and specialists, caregiving staff, associations, firms, governments, and the media – on the patient's behalf.

Patients and healthcare professionals lie at the core of patient-centric chronic disease management. Patient empowerment and participation – aside from being desirable – are necessary to ensure patients remain responsible for their own health management and decision-making. Healthcare professionals serve as close partners of patients, and focus on helping patients maximize their autonomy, thus enabling the effective implementation of self-care. However, when patients are not able to take care of themselves, caregiving staff can step in to assist residents to improve their health and well-being. Although they are not qualified to make medical decisions, caregiving staff visit the patients regularly, check their health status, build bonds with them, and remind them of various tasks in daily life. They also play a role in ensuring patients are encouraged to achieve prompt behavior change.

2.3. Chronic disease management: a process-based view

As persistent long-term illnesses, chronic diseases need to be managed by a combination of health interventions and lifestyle changes. The progressive nature of chronic illness means that care should be integrated across the continuum of the disease, including prevention and management of *comorbidities* that occur with the primary disease and the related complications that arise. Though different types of interventions and treatments have been studied and implemented, the ultimate goal for chronic disease management is to ensure medical compliance, and encourage healthier patient lifestyles. Thus, it is appropriate to focus on behavioral change.

The Prochaska and Velicer [6] stage model of a patient's sequence of activities in healthcare relationships consists of different behavioral stages that most people go through: pre-contemplation, contemplation, preparation, action, maintenance, and termination.[1] The model has been used to guide behavioral changes for smoking cessation [18], asthma management [19], and other issues. The patient's behavior and healthcare providers' expected actions in each stage are described next.

2.3.1. *Pre-contemplation stage*

In this stage, a person is not ready to change and may have never even considered adopting different behavior. The healthcare team (both healthcare professionals and caregiving staff) must increase the patient's awareness of the need for change, so she can begin to envision what making a change will be like. With an effective intervention, a patient can be motivated to seriously achieve the right kinds of changes [20].

2.3.2. *Contemplation stage*

In this stage, a patient begins to demonstrate behavioral changes within six months. She will be able to consider the costs and benefits of change, and decide whether to adjust her current behavior and comply with a treatment plan. The healthcare team can help the patient to understand the pros and cons of the current behavior pattern better, and the risk and rewards of making the associated adjustments to their lifestyle.

During the first two stages, healthcare professionals typically identify patients with a specific disease and ascertain related risk factors. Patient education programs can be conducted to raise the awareness of patients, and help them to get ready to make lifestyle changes. Caregiving staff, if there are any involved, should be informed about the risk factors and impacts of the chronic illness. Thus, in these two stages, caregiving staff and health professionals will play an active role in preventing potential illness. In this context, structured data analytics, such as segmentation [21], predictive modeling [22], and patient profiles, enhance their informedness about patients with a high risk of developing a specific disease or complications if they already have it. This target population can benefit from educational programs about disease prevention and management.

2.3.3. *Preparation stage*

People usually become ready to change their behavior in about 30 days, when they are involved in programs that involve some form of chronic disease management. They usually share their willingness to change with family or friends, despite their concerns about when to start, or whether they will be able to sustain the more desirable new behavior. The healthcare practice team can help to develop a strategy and an executable plan for change to engender patient commitment [20]. Practice guidelines are increasingly being utilized to support clinical decision-making based on evidence, and various decision support tools have become helpful for healthcare professionals to develop practical action plans for their patients [23]. In the Preparation Stage, the role of healthcare professionals and caregiving staff is to provide guidelines to help committed patients to develop an action plan.

2.3.4. *Action stage*

Once a patient enters this stage, she will begin to follow the plan that has been laid out for her treatment, and take steps to change her current pattern of behavior [6]. Patients with chronic diseases should be informed about medical treatment plans to comply with, follow medication instructions, conduct regular self-monitoring, and adopt a healthier lifestyle. Caregiving staff should be informed about the plan, and the key indicators of behavior change. The role of healthcare professionals is to monitor, support, and revise the plan, if necessary, in a clinical setting [20].

2.3.5. *Maintenance stage*

When they arrive in this stage, patients will have integrated new behavior into their everyday lifestyle. Healthcare professionals now need to provide sufficient monitoring and support so patients will not fall back into old behaviors or reduce compliance. For example, a diabetic patient who manages his blood glucose level well over some period may decide to skip taking medication or begin to perform blood glucose tests less frequently. To address issues that arise for patients in this stage, an explosion of health monitoring apps and tools has appeared. These are designed to provide healthcare professionals and caregiving staff with a clear understanding of the patient's condition and the extent of their compliance so early intervention can occur, as needed.

2.3.6. *The healthcare stage model overall*

The model's distinct stages may not occur in a linear fashion. For example, patients may not move into the Action Stage after going through the Preparation Stage, and instead, may return to the Contemplation Stage or even the Pre-contemplation Stage. Peer support is important throughout the entire process of behavioral change, and sentiment analytics can be used to understand patients' experiences based on their posts in online support groups [24].

Current chronic care practices emphasize the effectiveness of intervention programs, but tend to neglect the fact that a patient's behavior may change continuously. Therein lies an opportunity for a variety of data analytics to support this kind of healthcare.

2.4. *The Theory of Informedness*

2.4.1. *Key constructs and main proposition*

The theory of informedness has proven to be a useful theoretical orientation in multiple IS research settings, some of which have been especially influenced by data analytics. These include consumer marketing [25], digital entertainment [26], and household recycling [27, 28]. This approach is also beginning to be applied in analyzing residential energy use [29,30]. Similarly, doctors and healthcare staff need to be equipped with information that enables them to make the most beneficial forward-looking decisions [31], and relevant information must be available to patients [32,33].

The critical role and value of information data analytics are often acknowledged [34,35], and a growing number of research studies has measured the impact of information availability. *Informedness* refers to the state or quality of being informed. Widely used in IS and marketing research is *consumer informedness*, which more specifically refers to the degree to which consumers know what is available in the marketplace, including the precise attributes of different products and services [36].

The main proposition of consumer informedness theory is that improved consumer informedness influence the perceived value of the product, and thus consumers' aggregate willingness-to-pay [37]. Different levels of informedness affect the sequences of actions that consumers make, and which lead to their purchasing decisions [26]. The studies of different authors have found that the decision-making styles and efficacy of differentially-informed consumers may vary [38–41]. Further studies built upon the theory of informedness also suggested that informedness of different stakeholders involved with producing or using a product or services work together to co-create their value [42].

With a similar view, we believe that the informedness of different stakeholders of chronic disease management contributes collectively to the efficacy of chronic care. In this study, we define *healthcare*

[1] All of the comments that we have made in this section of the article related to the various stages of a chronic disease patient are tied into the various perspectives primarily drawn from the Prochaska and Velicer [[6]] stage model. We do not repeat this citation for each of the stages that we discuss for brevity, and to focus the discussion on others' contributions.

informedness as the state and quality of information provided to patients, healthcare professionals and caregiving staff to enable their decision-making, and empower them to act to manage their patients' chronic diseases more effectively. With advances in telemonitoring tools and IoT technologies, even minor changes in patients' activities and health can be tracked and interpreted. However, when they are given large amounts of data about their patients, caregiving teams can face the challenge of overwhelmingly big data, and they may experience an inability to filter out the most useful information to support their selections of the right actions to take. Additionally, as the chronic disease management model consists of multiple stakeholders, each may have their own priorities and action preferences.

3. Data collection, analysis approach and background of the cases

To answer the research questions, we adopted a qualitative research approach with a multiple-case design. The method is appropriate for our study for several reasons. First, case research is used for studies that examine "how" research questions [43–45] and suits studies that seek to understand a given phenomenon from a process perspective [46]. Our study examines a "how" question and delves into the process of chronic disease management. Second, case studies also are effective in gaining a deeper understanding of a phenomenon and its complexity in its unique context [47]. Since the employment of data analytics in the different stages of chronic disease management for different stakeholders is complex and multi-faceted, the case study approach supports an in-depth examination of the phenomenon and the interpretation of the shared understanding of the relevant stakeholders. Third, a multiple-case design is appropriate for obtaining a reading on the different forms of information and decision support systems used in the chronic illness management setting.

Given our research focus, we selected cases based on two criteria: (1) recent IS implementations using data analytics for chronic disease management and health improvement; and (2) those which involved either or both healthcare professionals or caregiving staff as system users, and patients too.

We obtained access to three field sites with IS implementations for chronic disease management to match the case selection requirements. These cases have similar characteristics in that they focus on chronic disease management, and involve both patients and healthcare service organizations. There are also variations in the three cases, including that the patients are at different stages of their chronic disease management process, and different data analytics tools are used to address the varying goals. The cases cover typical chronic disease management scenarios, including preventing discharged patients' readmission to the hospital, monitoring elderly people's daily activities, and tracking patients' vital signs when they are at home. We were able to access the cases from the beginning of the projects' implementations, so rich details were captured along the timeline of the healthcare process.[2]

We next offer case descriptions for the projects, so the reader will understand the settings and data, as well as the informants we relied upon. Project A was an IS for trained volunteers to assist at-risk residents in the community. Project B involved a mobile app and a dashboard to analyze data captured from a cyberphysical sensor-enabled monitoring system for elderly people in a community. It captured and analyzed their living patterns and detected abnormalities. Project C is a self-tracking tool for kidney patients undergoing *peritoneal dialysis* (PD). Patients were asked to enter their vital signs through a mobile app every day, so that the physicians and nurses could access them through a dashboard.

3.1. Data collection

Multiple sources of data were collected for the study, including software development documents, system architects, and personal interviews with software developers and various stakeholders, each consisting of 30−45 min duration. A detailed summary of our data sources is shown in Table 1.

Table 1
Data collection for the study.

Project	Systems	Stakeholders	Documents	Interviews (#)
A	Community healthcare IS	- Caregiving staff - Patients	- Software requirement specifications - Software developers' meeting memos with the CCT - Software development project Gantt chart	- Software developers (2) - Community volunteers (2)
B	Cyber-physical sensor-enabled home care for elderly	- Caregiving staff - Patients	- Software requirement specifications - Software developers' meeting memos with - Voluntary welfare orgs - Voluntary welfare org's meeting memos - Software development project Gantt chart	- Software developers (2) - Community volunteers (4) - Elderly residents (2)
C	Remote monitoring systems for dialysis patients	- Healthcare professionals - Patients	- Software requirement specifications - Software developers' meeting memos with physicians and nurses - Software development project Gantt chart	- Physicians (1) - Patients (2) - Nurses (1)

3.2. Data analysis approach

We examined data to determine caregivers' and health professionals' different needs for informedness at various stages of their patients' chronic illnesses. The project development documents provide background information for interpreting the interview data. Interviews were audio-recorded and transcribed for analysis, and the transcripts were analyzed using a *thematic analysis coding* technique [48], in which codes

[2] We did not have access to a large population of cases, so the most rigorous form of cross-case analysis was not available to us. Although our choices represent elements of these principles of case selection, other aspects of the study were externally funded and sponsored, so our use of the case study settings was also opportunistic and appropriate in the Singapore context based on the funding agencies agreement. Yet, it would be a stretch to argue that the cases were "most-different" or "crucial" as natural experiment settings. Singapore is too small a place, with too centralized a healthcare system and funding process for research to make such wide-ranging access possible. Our approach, thus, was realistic for the national setting.

were developed to identify categories (preset based on the interview questions or for new categories from the data).[3] After an initial round of coding, the codes were reviewed, combined into a master list, and then further analyzed to identify code families that directly mapped to different categories of healthcare providers' actions. Table 2 shows samples quotes of text fragments, however, we suppressed information about the initial codes, and only show the actions' purpose.

3.3. Case descriptions based on ongoing projects

3.3.1. Case A. Community healthcare IS

This volunteer-based community healthcare project was initiated by a regional Singaporean health system. It aimed to improve the community care program for high-needs clients or patients (which we will refer to as *patients* for consistency hereafter, except in interviews where the term *clients* was used), vulnerable elderly persons, and at-risk residents, who are referred as *frequent flyers* by hospitals and other local health services. Its goals were to monitor the status of these patients, provide early intervention, and prevent repeated hospitalization.

When the Community Care Team (CCT)—which was sited full-time within a specific neighborhood and included staff with healthcare or social work backgrounds—receives a referral, they visit the patients discharged from the hospital and who must live with certain conditions, to assess their social and medical needs. The CCT team has worked with volunteers, who received targeted training and are matched to specific patients, to help stabilize and monitor their conditions. The volunteers thereafter supported and monitored each patient's recovery. Follow-up home visits and calls typically are made to monitor the health status of the patient. This support had no time limit and continued for as long as the patient needed it. Patient encounters were documented using paper-based forms and notebooks. We learned from the manager of the CCT, who runs the program, that:

> "Residents who need help are typically the frail elderly, who have a combination of needs beyond medical [needs], which can include a lack of assistance with activities of daily living, a lack of adequate caregiver support, or other social issues … The program aims to provide a combination of medical, social and practical support to keep clients as well as they can be at home."

An IS with data analytics features was developed for the CCT to organize and track the status of the patients, manage the process flow, and provide them with plan-based monitoring in community care. The system reminded volunteers about field visits and phone calls, using pop-up alarms in their Android tablets. The input to the system consisted of two kinds of data. (1) *Structured data* enable the healthcare team to track a patient's demographic information, accident and emergency (A&E) department admission history, medical conditions, and so on. It also included: (2) *Unstructured data* is free text input from patients, and the CCT and volunteers (caregiving staff). The data analytics were used to populate an evidence-based care plan, and report on a number of patient-relevant parameters.

The patients in the program were mostly diagnosed with some chronic illness, or they had recovered from an acute illness. They understood what to do after being discharged from the hospital and had previously obtained professional advice on their medication regime. They also were mostly in one of the two action and maintenance stages, as they needed to take medicine regularly or keep an active living style to prevent their illness from recurring. The system was intended to improve the CCT's informedness about patients' condition sand their visit schedules. It also enabled the CCT's prompt action based on personalized care plans and the scheduled visits. However, the system only served to passively review a patient's status periodically. It was not able to provide enough actionable information to the volunteers regarding a patient's change in health behavior (e.g., from compliance to less compliance). The patients were also not informed about any changes in their health condition until the volunteers' next visit. One of the CCT members, who spoke with a patient, admitted:

> "I think the seniors really need a companion, other than just a regular health check-up for them …" and "the information from the system does not reflect their needs for social support."

Table 2
Actions during chronic disease management.

Actions	Purpose	Sample Quotes
Short-term	Understand patient compliance	*The system provides an effective way to check whether the patients have done their dialysis on the required schedule.*
Short-term	Provide prompt intervention	*After we see them (patients' health indicators), we may call them (the patients) to readjust the dialysis regime.*
Surrogate	Tell patients what to do	*Our senior citizens get confused with the medicines they brought home (after visiting clinics), and they need us to help review the introduction and tell them how to use the medicine again and again.*
Surrogate	Remind patients about consultations	*We will remind them to visit their physicians for regular check-ups.*
Long-term	Build bonds with patients	*Yes social support, yes and I think the seniors really need companions.*
Long-term	Understand common problems of patients	*Keep recording the health indicators is important for the dialysis patients, and we how we can help them remember to report the data.*
Long-term	Develop education and prevention programs	*If we knew many male elderly go to toilets more often at midnight in our suburb, we would like to organize a talk on prostate cancer.*

Note: Some quotations have been edited to enhance their readability in English, with care given to not changing the essential meanings that the interviewers were able to draw out. This is a requirement from the journal publisher to enhance the quality of international research content throughout its publications. The interviewees' recordings reflect the multi-ethnic and multi-lingual backgrounds of Singaporeans.

3.3.2. Case B: cyberphysical sensor-enabled home care for the elderly

In collaboration with data scientists, government agencies, health service providers, and voluntary welfare organizations, Project B was designed and developed as a cyberphysical sensor-enabled home solution. It is composed of fixed and mobile sensors customized for older people living alone in the community, to capture and analyze their living patterns and detect abnormalities. The project aimed to build intensive home-care surveillance to prevent hospitalization and lessen *morbidity rates*, the frequency that a disease appears in a population, among elderly patients with chronic diseases. The project targeted providing a better understanding of elderly patients' living patterns and responding to emergencies more effectively.

By the time we wrote this study for publication, cyber-physical

[3] Gioia et al. [[69]] have written extensively on the critical importance of coding as a basis to go beyond the often-perceived lack of rigor of qualitative case studies. Instead, they report on a more effective analysis approach. They created a basis for first-order coding that supports second-order theoretical theme and dimension identification. They make it possible to assert that there is a grounded-theory understanding about the real-world processes that have been revealed. A related argument is that the discovery process must be honest enough in real-world, real-people, and real-world processes terms so that it effectively represents the real-world setting for which a theory has been developed [[70]]. And the potential pitfalls and shortcomings must also be understood by the researcher [[71]]. This was the motivation for some of the work we did to create a basis for understanding the chronic disease care management setting.

sensors had been installed in 20 households, each with one elderly person living alone. The patient's movements in the living room, bedroom, kitchen, and bathroom were captured by *passive infrared* (PIR) sensors. Whether elderly patients had left their house was also monitored by door sensors. If no movement was detected over a predefined period of time, an alert was sent to the volunteer management team member's mobile phone. The volunteer manager then assigned a volunteer to go and check on the elderly patient's status. Most elderly participants have multiple chronic conditions they must manage, such as diabetes, hypertension, and other illnesses. They are also quite vulnerable to other chronic illnesses, especially because some illnesses may have significant comorbidity, as has been observed in India [49], Singapore [50], and elsewhere around the world [51]. The program participants were at various stages of chronic illness, ranging from pre-contemplation to maintenance.

Data inputs acquired in the project include: (1) structured data that cover the patients' demographic information and health status, and caregiving staff's demographic and contact information; (2) unstructured data on the staff's notes uploaded through a mobile portal; and (3) sensor data captured by PIRs and door sensors installed in each elderly patient's home. Data analytics are currently used to understand the living patterns of the elderly people, and to detect nonmovement and other anomalies. The analytical techniques used were machine learning and predictive modeling.

With the implementation of the project, the volunteers and their organization can now take care of more elderly people in the region. The elderly participants also reported an enhanced sense of safety with the program. However, the caregivers indicated they were more inclined to leverage the technology to suit their informational needs rather than being led by the technology, allowing them to change how they supported the elderly. Among the issues raised were the reliability of the system, and what the technological infrastructure could enable, such as delivery of better services, as well as delivering their services better. The caregivers sought to accomplish that by providing more information to the elderly so that staff from the caregiving organization can plan health promotion programs or other outcomes, such as social activities, that respond to the information provided by the system.

This set of results showcases the caregivers' appreciation of the potential of the technological infrastructure, but did not think it should dictate how they delivered services to the elderly. They saw it as playing an enabling role that could significantly improve how caregivers assist the elderly. In essence, they conceptualized the technological infrastructure primarily as a platform that enabled them to plan for long-term action, rather than as the solution.

In the early days of the project, the caregivers found the non-movement alarm to be very irritating. One software developer noted:

3.4. *"The caregiver organization complains about false alarms, and they want to make the threshold for the non-movement alarm longer."*

But actually, some were not false alarms …

"Then we did a simulation based on historical data. To see if we [should] adjust [the] threshold, [and] what will be the number of alerts generated for each elderly [person]. Then we adjusted the threshold for each individual to around 4–5 h."

Although the caregiving team reported feeling safer knowing their patients were monitored by sensors, they still expressed feelings of responsibility and stress when taking care of the elderly people.

3.4.1. *Case C. Health indicator tracking tool for kidney patients*

End-stage renal disease is the most severe form of chronic kidney disease, and patients suffering from this condition have poor life expectancy if they are left untreated. Patients who are not suitable for a transplant must remain on dialysis for the rest of their lives, which is an essential life-prolonging treatment modality. Dialysis replaces kidney function through the removal of accumulated metabolic waste products by a diffusion process, as well as through the removal of excess fluids from the body through ultrafiltration [52]. Dialysis can be performed in two ways: peritoneal dialysis, which uses the patients' own peritoneal membrane; and hemodialysis, which uses a synthetic membrane for diffusion and ultrafiltration to occur. Different perspectives exist on the efficacy of each for beneficial survival effects [53].

Project C is a remote-monitoring system developed for kidney patients undergoing PD. It consists of a mobile app and a dashboard. The mobile app was programmed to be compatible with some medical devices to automate the self-reporting process. For example, when patients had their blood pressure and weight measured, the data were automatically transmitted to a mobile phone through Bluetooth. The rest of the health parameters need to be entered manually into the system by patients. Altogether, there are seven indicators to be reported by them, including body temperature, body weight, blood glucose level, blood oxygen saturation level and pulse rate, dialysate fill volume during inflow and outflow, and the turbidity of the dialysate solution.

The dashboard allowed the doctors and nurses to view their patients' health status in real time, and use this information to set the rules and frequency for each patient's self-monitoring plan. Abnormal situations were highlighted for early intervention. Typically, data analytics have been used to detect abnormalities in patients' health status to achieve improved remote patient monitoring and analytical feedback to promote self-disease management.

Input to the system included: (1) structured data on patients' information, doctors' specifications of patients' parameters to be recorded, and their measurement frequencies; and (2) mobile data on patients' health indicators from medical devices and self-reported data through mobile phones.

The system has been effective in general. As kidney patients were mostly in the action and maintenance stages, they received regular reminders from the application to report their health indicators. Some patients found the reminders irritating and intrusive to receive when they were not at home. Nurses reported that reviewing the dashboard added extra work:

"We need to attend to all the patients in the clinic first at work, and only have time to view the dashboard at break."

They also reported stress in taking care of patients in real time:

"We feel additional responsibility in taking care of the patients using the system … as they may expect you to read the dashboard all the time, which is not true."

A summary of the three cases is provided in Table 3.

4. Primary case findings

By synthesizing common observations from the three cases and comparing the differences between them, we can formulate findings related to the informedness needs of healthcare professionals and caregiving staff for chronic patients at different stages of their illnesses. Our findings are based on evidence related to our two research questions, which are both related to technology. We obtained sufficient input related to these questions to offer insights regarding the different roles that healthcare professionals and caregiving staff play, and the immediacy of informedness in their decision-making.

Our results demonstrate how data analytics were being used, and how they were received by different healthcare stakeholders. However, it was necessary to make inferences about how data analytics can be improved to create more beneficial impacts for all stakeholders, and how this relates to the informedness needs of healthcare professionals versus caregiving staff for different stages in chronic disease management.

Table 3
Summary of the cases.

	Case A	Case B	Case C
Description	- Community healthcare IS	- Sensor-enabled elderly home care	- Remote monitoring systems for dialysis patients
Data source	- Evidence-based care plan - Analytic reporting for different parameters	- Structured data: Users' demographic info and health status and caretakers' demographic/ contact info - Unstructured data: caregiver's notes sent via mobile portal - Cyber physical sensor data: captured by PIR sensors in houses of the elderly	- Structured data: patients' info, doctors' input of patients' recorded parameters and frequencies - Mobile data: patients' health indicators from medical devices and their mobile phones
Data analytics	- Evidence-based care plan - Analytic reporting for different parameters	- Understand living patterns of elderly patients - Detect non-movement and other anomalies	- Remote patient monitoring - Self-disease management
Context	- Used for maintenance	- Used in Pre-contemplation, Contemplation, Preparation Stages	- Used for Action, Maintenance Stages
- Patient informed ness	–	–	- Health status - Self-report schedule
- Caregiving staff inform-edness	- Patient health status - Visit schedule	- Anomalies in patients' activities	–
- Healthcare professional informed ness	–	–	Patients' health status
Observations	Lack of understanding of behavioral changes until readmitted to hospital	- Info recommended for action; did not provide context info; lacked implica-tions for actual health behavior - Caregiving staff wanted to know how to provide better service; and not be reminded by alerts	- Not able to customize reporting plan for patients' activities - To ensure patient safety, nurses worked harder to respond to the results

4.1. How data analytics support healthcare providers' informedness

To answer this question, we noted several common findings across the three cases to interpret how analytics can be used to support the varying informedness needs of healthcare professionals and caregiving staff. Our discussion is focused on support from data analytics.

Our first overall observation from the case study interviews is:

- **Finding #1 (Informedness for Short-Term, Long-Term, and Surrogate Actions)**: *Healthcare data analytics support should balance the different users' levels of informedness in terms of their need for supporting long-term, short-term, and surrogate actions.*

Healthcare professionals and caregiving staff seem to require different levels of informedness to support various actions in their caregiving roles. As the recipients of data analytics, healthcare professionals' and caregiving staff members' need for information and high immediate informedness is driven by their intended actions in helping patients [18]. Our interviewees in Cases B and C were all willing to receive information useful to manage a large cohort of patients, instead of attending to individual-level health condition changes. The nurses and physicians in Case C expressed the feeling of being overwhelmed, however, with prompts telling them about the abnormal status of the dialysis patients they were monitoring. A nurse in Case C mentioned, for example:

> "Real-time alerts on patients' condition bring a lot of stress to the colleagues on duty, as we need to attend to the patients visiting the clinics too."

Although reacting to troubled dialysis was indeed their initial goal when using the remote monitoring system, having rich information to understand their patients' long-term status with different treatment plans was more important. Caregiving staff in Case A also mentioned that the system did not provide actionable information regarding their patients' health behavior changes.

The theory of informedness in other settings suggests that the enormous range of information that is readily available to consumers and other decision-makers has an impact on their choices of products and services [56], as well as on their in-home decisions to recycle hazardous waste [27]. In the context of chronic disease management, where a huge amount of data about patients can be collected, the delivery of these kinds of micro-level information may overload healthcare professionals [58]. Thus, we believe that in order to provide the required level of informedness, data analytics support should not just aid the actions that have require promote response and short-term impact. It should also drive actions that have long-term impact and lead to a well-designed prevention program or more effective intervention strategy.

Our next observation from this research is:

- **Finding #2 (Stakeholder Actions for Patients at Different Stages of Behavioral Change):** *Healthcare data analytics support needs to enable different stakeholders' actions related to taking care of patients at different stages of behavioral change.*

In our case analysis, we found that data analytics tools are still being developed and continue to be used in silos, assuming that patients' needs are static. However, according to the transtheoretical model of behavior change, patients constantly move from one behavioral stage to another [6,59]. Even patients already in the Action Stage may lose their motivation and become less compliant to the behavior change strategy. In Case C, the self-monitoring apps based on smart phones were only effective in detecting anomalies when patients recorded their health-related data regularly. If patients felt the process was troublesome, and recorded less often than was required or recorded only when they felt well, the information generated would not be useful. Ideally, data analytics tools should allow healthcare professionals and caregiving staff to evaluate when patients are regressing from the Action Stage to the Contemplation Stage. The early detection of diminished patient commitment will allow the healthcare team to redesign the intervention program accordingly. This is another role that data analytics can play to assess a patient's progress through the stages of behavioral change for improved chronic disease management.

As a result, different data analytics support is required in general, and there appear to be further differences relative to healthcare professionals and caregiving staff. As every caregiving staff member is in charge of multiple patients at different stages at any point in time, the data analytics that are used should support their different actions in helping each patient. This is also true for healthcare professionals, who face the necessity of changing treatment regime decisions at different times across the chronic illness stage spectrum [18].

This leads to our third observation from this research:

- **Finding #3 (Improved Stakeholder Capabilities):** *Healthcare data analytics should support what is necessary for the desired level of different users' informedness, which must leverage stakeholders' capabilities better.*

The three cases reveal that it is important to understand informedness from data analytics and the capabilities of healthcare providers. The power of both is leveraged on behalf of patients as a best approach in chronic disease care management. In other words, the level of informedness of data analytics and service protocols should take advantage of the capabilities of IT and the resources of prospective users. This ensures that the technology platform is not seen to direct healthcare providers' actions overall, but rather to enable more effective delivery of services and encourage better service efficacy.

The design of the informedness of data analytics, then, must consider the potential resources that can be leveraged. In Case B, strong volunteer support and clear communication among voluntary welfare organization team members were essential for designing the notification protocols according to their level of urgency, and allowing staff to take turns responding to notifications from the home monitoring system. The manager of the volunteer welfare organization mentioned that all the staff have passion for their work, and they leverage neighborhood support to respond to notifications of abnormal cases.

"I think if it's an emergency, we wouldn't mind, being in this field (after office hour/ over the weekend), we are also willing to step forward to help… They (the neighborhoods) have common corridors so that has been quite helpful…"

In Case C, limited human resources in the clinic constrained the use of abnormality detection analytics for real-time monitoring of patients. As the physician said:

"We don't have enough manpower to monitor the health status of all the dialysis patients in real time."

Our fourth overall observation is presented next:

- **Finding #4 (Interference from Patients' Expectations):** *The data analytics support for the desired level of different users' informedness should consider potential interference from patients' expectations.*

The patients we interviewed felt safe and cared for, knowing that healthcare professionals were always watching them using technology. However, healthcare professionals reported feeling greater responsibility and stress for taking care of patients.

In Case B, for example, the caregiving team asked software developers to adjust the threshold for which alarms were generated based on non-movement detection within an elderly patient's residence several times. In Case C, a physician told developers that keeping track of patients' health status was important, and that he wanted patients to comply with the reporting schedule. This led software developers implemented reminder functions in the application. However, patients said that when they were outside of their house or having a conversation with friends, they found the reminders to be "*irritating*." The data analytics were not customizable to permit the reporting plan to take these kinds of contextual factors into account. Thus, the analytical support based on the same set of data did not simultaneously support patients, as one kind of stakeholder, and healthcare professionals and caregiving staff as two other kinds of stakeholders.

So, we found indirect evidence of differences in the need for informedness-driven data analytics — probably across three different groups of stakeholders, rather than just two, as we initially imagined before completing a full analysis of our case studies.

4.2. How data analytics can be tuned for healthcare roles by patient treatment stage

We next will discuss the different roles of healthcare professionals and caregiving staff with reference to the stages in the transtheoretical model. This allows us to characterize healthcare providers' informedness needs based on a patient's behavior stage, as shown in Findings 5–9 in Table 4.

4.2.1. Pre-contemplation and contemplation stages

During the first two stages, the people that were cared for included patients diagnosed with a chronic disease and others with risk factors for one. In Case B, some of the elderly users were diagnosed with a chronic disease and were also carrying risk factors for other chronic diseases. The caregiving staff expressed a preference for being informed about individuals with high risk factors, so that they could provide better assistance to then. They also preferred to be informed about planning for actions that would have long-term impacts, such as actions that lead to major changes in intervention strategy or that target a wide population rather than individual patients. The caregiving staff we interviewed were interested to know about the existence of a particular risk factor in a neighborhood or among a certain group of people, so they can provide targeted health education programs. For instance, a staff member stated:

"If we know many male elderly go to toilets more often at midnight in the region, we would like to organize a talk on prostate cancer."

Caregiving staff, we learned, value information that can help them organize health and well-being programs to create more beneficial effects. Despite the large amount of patient data captured, they were looking for greater autonomy in providing help to patients, rather than being driven by the information. This meant that not all the informedness that the system created was relevant for them. For example, the manager of the community volunteers in Case B mentioned that:

"We actually hope that the rich amount of data collected could tell us how to improve our services to our seniors."

To achieve the long-term goal of improving the caregiving staff's service provision, the data analytics should convey a higher level of relevant *relative informedness* for the roles they play, such as aggregating data to identify common concerns of patients in similar age groups

In our cases, no healthcare professionals were involved in the Precontemplation or Contemplation Stages, thus their needs for informedness remain unclear. This is also because the healthcare system in Singapore is more reactive than preventive. Based on our literature review, we believe that healthcare professionals are interested to be informed about aggregate information related to the distribution of a disease and the related risk factors [6,20]. See Finding #5 in Table 4 (above) for the Pre-contemplation and Contemplation Stages.

4.2.2. Preparation stage

In this stage, healthcare professionals and caregiving staff help patients to develop a strategy and executable plan for change to engender their commitment. This stage is a short period of time in the overall chronic disease management process, as once patients have begun behavioral change they enter into the action or maintenance stages [6].

When patients in Case A were discharged from the hospital, they were given medical advice by their physicians. Those physicians were not directly interviewed, as they were not the users of the system we studied. According to the literature, the role of healthcare professionals is to provide standard guidelines to patients so they can adapt to them in their daily lives [17]. In Case A, the CCT also created a personalized intervention plan based on its initial assessment of patients' conditions. See Findings #6 and #7 for the Preparation Stage.

Table 4
Different needs for informedness by healthcare role.

Roles	Pre-contem-plation	Contem-plation	Preparation	Action	Maintenance
• **Note:** All findings in the entries below are related to professionals or staff being informed about an opportunity or an action that will result in improved patient healthcare and well-being.					
Healthcare professionals	–		**Finding #6 (Healthcare Professionals, Prep Stage):** They require informedness about the best medical treatment plan for their patients' well-being.	**Finding #8 (Healthcare Professionals, Action and Maintenance Stages):** Be informed when to: - Promptly intervene if complications arise - Revise the treatment plan as appropriate	
Caregiving staff	**Finding #5 (Caregiving Staff, Early Stages):** They must be informed about: - Individuals with key risk factors; and - Population and regional risk factors that affect the care they give.		**Finding #7 (Caregiving Staff, Prep Stage):** They must be informed about how to craft a personal intervention plan for individual patients.	**Finding #9 (Caregiving Staff, Action and Maintenance Stages:** Be informed when to: - Remind patients of treatment plan - Remind and reinforce patients' behavior (surrogate role) - Interpret key indicators of behavior change - Monitor / support patients and revise plan when necessary	

4.2.3. Action and maintenance stages

Chronic disease management requires a long-term commitment from both patients and their healthcare team [1,14]. Most of the patients in our three cases were in the Action or Maintenance Stage, and remote monitoring was the most widely-used way to provide continuous monitoring and support for these patients.

We found that healthcare professionals' needs for informedness focused on driving actions leading to prompt intervention in patients' disease management regimes, and required patients to make immediate behavior changes (*short-term actions*). In Case C, for example, the nurses typically monitored changes in patients' health indicators, and tried to provide prompt instructions, such as "*changing dialysis fluid*" (which can have an immediate impact on a kidney patient's health). The physicians and nurses also expressed their need to be informed about whether there was any sign from them to *"change to a different intervention strategy"* (*long-term actions*).

Similarly, the caregiving staff also expressed a need for informedness to enable prompt intervention with patients. The caregiving staff in Case B, for example, were responsible for elderly patients' safety in response to the non-movement detection alarms sent to the staff. The caregiving staff in Case A actively visited patients and directed them to visit a clinic, if any complications were identified.

In our research, the caregiving staff also noted that patients sometimes forgot the details of the care information they received. Many patients have low IT literacy or health literacy, and are not able to act upon useful information directly. The patients in Cases A and B, for example, had at least one type of chronic disease and one had eight concurrently. Also, some patients mentioned that they could not remember what time to take their medicine — and sometimes forgot which medicine to take. They also forgot when to refill their medicines and the time of the next appointment with their physician. Even when a text message was sent to their phones to remind them, they often misplaced their phone or forgot again after seeing the message. The caregiving staff in Case B also mentioned:

> *"We would like to know when our clients need to visit the clinic again, so we can remind them and arrange transportation for some of them."*

Thus, there must be some capability for caregiving staff to identify whether patients are carrying out appropriate actions so the desired behavior is not compromised, especially for aged patients, or patients with cognitive impairment. Caregiving staff also need to be informed about when to perform *surrogating actions* to assist patients with self-care activities.

Based on our analysis, the different urgency of decision-making that exists for healthcare professionals (especially physicians and nurses) means they must be as completely informed in as up-to-date manner as possible. Healthcare professionals are likely to need more specific data [54], as we described for each of the case system inputs, in order to make immediate sense of a patient's situation. This allows them to determine whether to medicate the person differently, operate on them, or hold the course based on the past treatment regimen. As the physician in Case C mentioned, the top priority is to *"ensure the safety of the patients"* undergoing dialysis, thus *"prompt reaction"* is necessary. Since patients have fewer chances to meet with healthcare professionals, the informedness of these experts in office visits and consultations is critical.

For caregiving staff, there is a different level of immediacy, since they are ultimately not responsible for signing off on specific forms of treatment for patients, or making changes in their medication regimes [55]. Caregiving staff informedness needs to be tempered primarily by the relevance of their short-term procedural needs (e.g., equipment breakdowns, immediate patient visits), while their long-term needs are for planning rather than directly shouldering the responsibility for patient health outcomes.

Of course, both kinds of stakeholders are similar in their need to communicate directly with patients [18,55]. This promotes the need for *relevant relative informedness*, a concept that builds on earlier theoretical work in the IS literature that characterizes different kinds of consumers as having somewhat different information needs [25,56,57]. See Findings #8 and #9 for the Action and Maintenance Stages.

We summarize our overall findings in Fig. 1 with a framework for healthcare informedness.

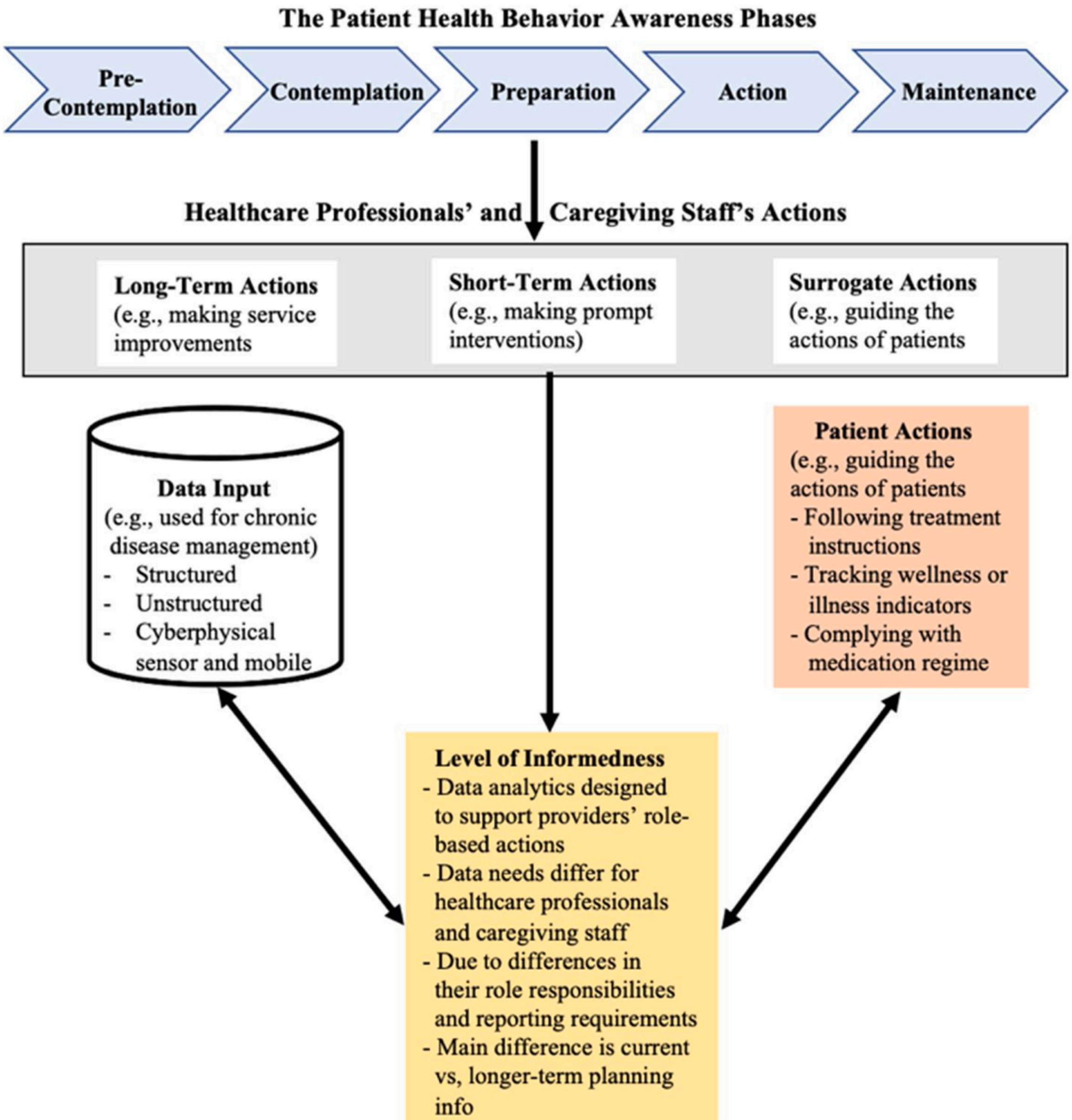

Fig. 1. A Framework on Healthcare Professional and Caregiving Staff Informedness.

5. Discussion

By drawing upon the transtheoretical model of health behavioral change, the theory of informedness, and insights from case studies, we have sought to make theoretical and practical contributions.

5.1. Research contributions

First, this study contributes to the development of the theory of informedness. The theory states that information receivers' decision-making performance is based on the amount and quality of information they receive, so they can select among different action choices in a specific applied setting [25,27]. It also implies that with more and better-quality information, people can make better decisions that create value and more beneficial outcomes. However, in the present era of big data, more detailed, granular and frequent information may not lead to better decision-making.

Our study also reveals that healthcare users provided with real time information may experience stress and anxiety in reaction to that information – an unintended consequence of the increasingly high-tech work environments in Singapore. We also found that the provision of data analytics support should be motivated by a user's needs for informedness, since each has a different role and action choices they hope will have the desired impacts.

Second, we delved into the different types of actions that can be supported by data analytics in a chronic- disease management setting. We identified actions that lead to immediate changes, have long-term impact, and surrogate actions that may be taken on behalf of other people. This range of actions is characteristic of many service settings, and should be viewed as quite general and not healthcare-specific. This is an unexpected conclusion from this research.

We also discussed how different types of actions can be supported by different types of data analytics. Actions that lead to immediate change can be supported by real-time information, taking into consideration the capabilities of the information recipients. Actions that lead to long-term impacts require data analytics information that filter out less-relevant and distracting micro-level details. They also require aggregate findings to be assembled into meaningful guidelines and insights.

Actions on behalf of other people, meanwhile, need to be carried out based on data analytics-driven informedness, when it is clear that conducting the related actions will add value beyond their potential social costs. The healthcare news is replete with stories on the *unintended effects of overtreatment* on the part of well-intentioned healthcare service providers: when a patient has not explicitly communicated that he or she specifically wishes to receive such help. This is similar to the clinical, social and cultural iatrogenesis of the past, which put medical norms ahead of patient permission and the rise of the current *epidemic of overtreatment* [60,61].

More generally, our classification is applicable to other contexts, such as organizational decision-making, marketing, and public service. Additional contextual use of our ideas will enrich the development of informedness theory through new applications of the data sources and analytics discussed.

Third, this study bridges health education and promotion theories, and the findings of IS studies to provide new insights on data analytics for chronic disease management.[4] Despite the penetration of data analytics in various domains of healthcare [8] – especially genomics and gene analytics, population anomaly discovery, and *functional magnetic resonance imaging* (fMRI) among others – few researchers have investigated how data analytics can be used to support intervention in the typical daily activities of healthcare providers. Our study distinguishes between the kinds of information needed by healthcare professionals and caregiving staff. While healthcare professionals are more interested in understanding patients' health indicators and looking for improvements in their treatment, the caregiving staff's focus is on prevention and maintenance.

5.2. Contributions to practice

This study offers practical implications for data scientists, healthcare providers, and caregiving organizations interested in leveraging data analytics to improve the quality, targeting, and efficacy of their services. Although many new data analytics tools have been developed to support patients' behavior changes, and improve their health and well-being [8], the tools nonetheless may reduce the productivity of users in healthcare settings and caregiving organizations. Thus, data analytics tools should be designed with the everyday activities of all kinds of healthcare providers in mind. They then will be more effective, unobstructed by the technology, and able to benefit from the use of data analytics information structures that are suited in unique ways to the work they do. Such tools need to be designed for success-in-use, and not just for demonstrating the *limits-of-innovation.*[5]

This is especially true, we think, when considering an organization's capability and reconciling the multiple priorities that exist among its different stakeholders – all of whom are hoping for maximum performance in their technology-assisted work. As healthcare data analytics continue to build in importance, it ultimately must function as an "everyday thing" in chronic disease management to create informedness that is higher, more relevant, more frequently updated, and more attentive to patients' problems.

6. Conclusion

Chronic disease management is an important area of healthcare, since chronic disease creates high costs and affects the quality of life of patients [62]. Management of chronic diseases requires the collaboration of multiple stakeholders, including patients, healthcare professionals and caregiving staff. Many healthcare and caregiving organizations use data analytics to learn more about their patients in ways that are far less intrusive than data collection has been in the past [63,64]. However, in the big data era, the amount and types of data collected are increasing, and the information available to healthcare providers is greater than ever before. By leveraging the theory of informedness and the transtheoretical model of health behavior change, we identified several major findings relating to how data analytics should be used to support healthcare providers' information needs for chronic disease-focused healthcare. We did this through the use of multiple case studies on the implementation and usage of data analytics in different chronic disease management settings.

From its inception, our research was intended to inform both researchers and practitioners. Data scientists usually work with a problem-driven approach, developing techniques to address the problems that are most salient in their contexts of interest. We see a lot of interest from this community of researchers to develop new approaches, applications and knowledge for the healthcare context. Our work suggests that researchers should anticipate the problem of engendering compliance and beneficial behavior over time in chronic disease care, since the problems that patients face in the course of their disease tend to change over time.

Our discussion of data analytics in support of chronic disease management is incomplete without noting several limitations of the present work. One limitation is associated with the research methodology, since the case study method cannot justify causal relationships or provide statistical evidence on findings, although it can offer rich insights on a phenomenon. Second, the classification of the actions is drawn from the cases only, so there may be other types of actions performed by healthcare providers that we could not observe or classify in this research. Further study should explore different settings and scenarios to investigate whether there are other noteworthy but unclassified actions.

Another limitation is that one of the three cases presented in this article included both healthcare professionals and caregiving staff as end users at the same time, potentially limiting the direct comparison of the two roles. However, in some cases, both healthcare professionals and caregiving staff were involved in the system's implementation at the beginning. For example, in Case B, a physician from the regional hospital also worked on the advisory board of the project, providing

[4] Although we focused on the transtheoretical stage model of health behavior change, there are other appropriate lenses though which we could have viewed our chronic disease management context [[72]]. An example is *ecological models* [[73]], which view health behavior as being influenced by multiple levels of factors, including intrapersonal and individual drivers, and interpersonal interactions that create pushback or offer aid in behavioral change. Two other related kinds of factors are institutional and organizational, and public policy actions and programs. A second example is the *health belief model* [[74]]. This theory predicts that an individual's willingness to engage in beneficial health change behaviors is based on four psychological perceptions: of the disease; its severity, the person's susceptibility to it, and the benefits and barriers effective control that are present. In the theory, a patient's extent of *self-efficacy* is critically important [[75]]. Also, the patient must be prompted to take beneficial action – like being convinced that SPF 50+ sunscreen lessens the likelihood of skin cancer.

[5] The human-factors cognitive scientist, Donald Norman [[76]], referred to the *design of everyday things* and *instant usability* with no need for complex manuals and instructions. In simple new technology settings, many people who have no time or inclination to use manuals often never understand how to create the best outcomes with their use. The complexity of the healthcare environment is typically high. The risks associated with unintended care and errors in treatment are costly in human and financial terms too. Thus, healthcare data analytics will never be an "island apart from the mainland of practice."

guidance on monitoring and responding to elderly users' health conditions. In fact, it is common in the healthcare system that the role of caregiving staff is to reduce the load that physicians have to bear. Thus, both providers are not seeking the same type of informedness at the same time. As such, our findings may be strengthened if future research investigates cases where analytics are developed for both healthcare professionals and caregiving staff in different ways.

Finally, we wish to remind the reader that we considered the most important question of all: how can analytics support the different needs for informedness of healthcare professionals and caregiving staff? We also explored how healthcare professionals and caregiving staff differ in terms of what kind of information they require at different stages of chronic disease management, and how the appropriate data analytics can be enhanced to improve patients' health and well-being. This study is foundational in advancing the development of the theory of informedness and in providing practical guidelines to data scientists, and physicians, nurses, and related caregivers interested in leveraging data analytics to improve the efficacy of their services to improve patients' health.

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Appendix A. Key terms and definitions

Term	Definition	Comments
Chronic disease	Long-lasting conditions with persistent effects, usually longer than 3 months.	The 10 most common chronic diseases are: high blood pressure, Alzheimer's disease, heart disease, depression, arthritis, osteoporosis, diabetes, chronic obstructive pulmonary disease (COPD), cancer, and stroke [65].
Chronic disease management	An organized, proactive, multi-component, patient-centered approach to health-care delivery that involves all members of a defined population who have a specific disease or with specific risk factors.	The World Health Organization (WHO) has reported that 80% of heart disease, type 2 diabetes, and stroke, and 40% of all cancer are preventable by healthier diet improvements, more frequent exercise, and cessation of tobacco use [66].
Healthcare professionals	A physician, nurse, or other healthcare professional who is qualified by education, training, licensure/regulation (when applicable), and facility privileging, and performs a professional service within their scope of practice, and independently reports that professional service.	The reason that we do not distinguish among the different sub-roles of people involved in this group of healthcare professionals is because they all essentially involve in the same kind of decision-making process, so their needs for informedness are quite similar.
Caregiving staff	A staff member working in a volunteer-based community healthcare organization to provide assistance to residents to improve their health and well-being.	While all healthcare service staff members – doctors, nurses, specialists, surgeons, consulting staff and so on give care to patients, the critical distinction that we wish to point out for the caregiving staff group is that they all are volunteers.
Trans- theoretical model of behavioral change	A theory used to understand an individual's readiness to act on a new healthier behavior, and provides strategies, or processes of change to guide the individual. It looks at an individual's behavior change from a process-based perspective.	This model was developed in the 1980s at the University of Rhode Island. It emphasizes several constructs: stages and the process of behavior change, the decision balance for the pros and cons of changing, and confidence and temptation. Its constructs are drawn from different theories of behavior change, and hence, the descriptor "transtheoretical" is used to characterize it [59].
Informedness theory	A theory which states that truly-informed users of information are able to make better decisions among the actions, choices, and outcomes they have available to them for a given decision-setting, which enhances the value of their involvement in creating benefits.	Informedness theory has been used in multiple contexts, including accounting and finance, managerial decision-making, consumer marketing and e-commerce, environmental recycling, and residential sustainability, among other setting. A central goal, in IS research terms, is to figure out how to realize as much potential value from information and the technology that delivers it for use as possible [67].
Healthcare informedness	The state and quality of information provided to stakeholders (patients, healthcare professionals and caregiving staff) to enable their decision-making and empower desired actions.	This kind of informedness is specific to the healthcare context, where the information that is used by professionals and staff is quite different from what we have observed in other settings, because the responsibilities they have for patients also is quite different, especially for decisions and actions.
Healthcare professional informedness	The acquisition and application of information provided to professionals in a caregiving organization to make sense of their patients' health status so their decisions have more beneficial impacts on patient health.	Healthcare professionals must make timely decisions, for which they are ethically and morally bound, in their practice of medicine. Making decisions on the basis of appropriate and relevant information is intended to maximize the likelihood that a decision is viewed as correct for the patient, practice, healthcare organization, and anyone who may be asked to evaluate its outcome later.
Caregiving staff informedness	The acquisition and use of information provided to the staff in a caregiving organization to report the patients' health status and develop programs to improve patient health and well-being.	Caregiving staff do not have the responsibilities for decisions that will change a patient's short-term care, medication, or treatment approach. Instead, they offer services that support the larger healthcare setting, and its activities, and typically do not sign off on having treated a specific patient, as healthcare professional must.
Voluntary welfare organizations	A non-profit VWO provides welfare assistance or other services that benefit the community-at-large.	The organizations are usually set up in Singapore as Societies, Companies Limited by Guarantee, and Charity, involving a trust to obtain Institution of Public Character (IPC) status [68].

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.im.2020.103315.

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