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An Integrated Social and Behavioral System Approach to Evaluation of Healthcare Information Technology for Polychronic Conditions

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Abstract Healthcare delivery systems are evolving with the advances in health information technology (HIT) development and its applications to coordinated or guided care for polychronic conditions. The design features of artificial intelligence in healthcare reflect the public interest in optimizing care coordination and communication between providers and patients. This article offers a practical evaluation and assessment of the relevance of theoretical frameworks and appropriate methodologies to formalize a multi-criteria optimization of a logic model applicable for achieving the system's efficiency and effectiveness. In specifying theoretical constructs and evaluation methods for HIT evaluation, a three-fold purpose is to show the relevance of personal and behavioral determinants of HIT use, articulate the need for developing a transdisciplinary framework, and formulate appropriate multilevel modeling and causal analysis of the determinants of HIT use and its impacts on chronic care.

Keywords: Polychronic conditions, HIT evaluation and research, organization design and strategy, logic model in HIT research, transdisciplinary framework.

1. Introduction

There exists a critical need to improve design and evaluation processes associated with the development and integration of health information technology for chronic conditions. In this article the authors provide critical insights on this matter; thereby, elevating the body of knowledge associated with design processes in this field of research. A chronic condition is a disease or condition that usually lasts for 3 months or longer, as defined by the National Cancer Institute (National Cancer Institute, 2021). The U.S. Department of Health and Human Services (HHS) defines chronic conditions as conditions that last a year or more and require ongoing medical attention and/or limit activities of daily living (HHS, 2010). Chronic disease epidemiology is encumbered by variations in taxonomy and lack of a comprehensive list of conditions for reporting multiple chronic conditions. Globally, one in three adults experiences polychronic conditions, which emerges to be a critical public health problem (Hajat & Kishore, 2018; HHS, 2010; Wan, 2018b).

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Commonly known conditions include arthritis, diabetes, hypertension, and heart disease. The proportion of patients with 4+ chronic diseases is expected to be double by 2035 (Hajat & Stein, 2018; HHS, 2010). The burden associated with these chronic conditions is compounded by the lack for integration between primary care and speciality care. Thus, fragmented services may lead to confusion and medical errors (Hajat & Stein, 2018; HHS, 2010) and also cause significant strain on the patient as well as the healthcare system.

One relatively new disease management approach is that of using identifiable high users of health services. More specifically, this population-based management approach to target subgroups at the risk of experiencing complex needs for integrated care. For instance, they include:1) elders with polychronic conditions living independently in the community; 2) persons with functional limitations requiring long-term assistance; and 3) elderly patients making transitions across the care continuum, such as moving from a hospital to a rehabilitative facility after surgery. Thus, the management of specific needs for the targeted subpopulations is part of population health management (Wan, 2018d). Furthermore, health care management activities should center on the coordination and integration of population risk management, utilization review, quality management, value-based management, and patient engagement management.

Here it is important to specify theoretical constructs and evaluation methods for health information technology evaluation, with a three-fold purpose to show the relevance of personal and behavioral determinants of the HIT use, articulate the need for developing an integrated framework, and formulate appropriate multilevel modeling and causal analysis of major determinants of HIT use and its impacts on the cost and quality of chronic care. Furthermore, this article will explore the advancements needed to improve early identification, care management programs and delivery, and patient engagement strategies in improving the care delivery system. The development of a population health management approach requires the teamwork of scientists from multiple disciplines and the collaboration of the HIT industry free from inherent bias (Gurupur & Wan, 2020). The research activities will include to: 1) conduct clinical trial studies, 2) share and analyze metadata, 3) validate predictive models to guide the development of graphic-user interface for enhancing self-care management, 4) provide integrated care, and 5) use user-friendly Internet-of-Thing (IoT) technologies as key components for improving polychronic care and disease prevention. Additionally, the article also offers a practical evaluation and assessment of the relevance of theoretical frameworks and appropriate methodologies to optimize the power of a logic model applicable for achieving the system's efficiency and effectiveness. Ultimately, we will clarify how measurements of important variables and their causal structural relationships can be delineated and applied in empirical research.

2. Theoretical Import of Relevant Social and Behavioral Constructs for HIT Studies

HIT is the computer application of information processing that manages storage, retrieval, sharing and using health care information, data and knowledge for communication, and decision-making support. There are various technologies that are included as HIT to improve and transform healthcare by reducing human errors, increasing coordination of care by improving communication, facilitating changes in prescribing behavior, enabling to monitor changes by tracking data over time, encouraging the delivery of integrated care, improving clinical outcomes and patient safety, and enhancing efficiency and effectiveness in the delivery of appropriate care and services. Three popular theoretical frameworks in HIT are cited here to show how HIT has been scientifically designed and evaluated: HIT Use-Outcome Model, Technology Acceptance Model (TAM), and Health Belief Model (HBM).

The HIT Use-Outcome Model (Figure 1) demonstrates from a user's perspective for HIT use is preconditioned by three dominant contextual and ecological constructs, the predisposing factors (demographic, personal beliefs, and social class factors), enabling factors (health insurance coverage, access to a primary care source, availability of providers and HIT, etc.), and the need-for-care factors (observed and reported health conditions or health status). Empirical studies have confirmed the fact that the need-for-care factor is more influential in explaining the variability in health service and technology use, and outcomes (Andersen & Newman, 1973; Babitsch et al., 2012; Wan & Soifer, 1974).

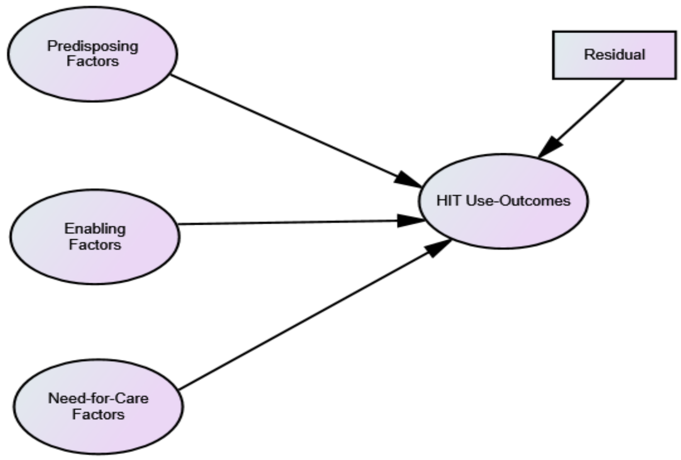

Fig. 1. A HIT Use-Outcome Model

However, the HIT Use-Outcome Model does not adequately address how to generate preventive practice behaviors that are influenced by improved disease knowledge, motivation, and attitude change. Three examples may demonstrate the importance of social behavioral factors that may influence health. First, athletes seek personal HIT to improve their physical development and health to reach the top of their sporting endeavor with peak performance. Second, patients who are frustrated with the inability to get a timely appointment with their healthcare providers push for personal HIT to get information about their condition that normally would be generated in the clinic/office. Third, people demand smaller, simpler, easier to use, less expensive personal HIT to satisfy their personal quests for better health outcomes and physical performance. The technologies include wearable blood glucose (HbA1C) measurement, pulse oxygen metering through a cell phone, Kardia-Mobile ECGs through cell phone, internet linked training/coaching technology like iFit, Peloton, Mirror, and even the adoption of Apple's FaceTime for telehealth visits. Personal and behavioral factors may be incorporated partially into the three dominant constructs of the model by usefully identifying the profiles of patients who are most likely to benefit from HIT. However, the model fails to analyze the interaction effects of these three factors on utilization behavior or outcome measures. Additionally, the analytical approach of the HIT Use-Outcome Model is often constrained by its cross-sectional study design. Therefore, there is certainly room for future studies to include longitudinal study designs.

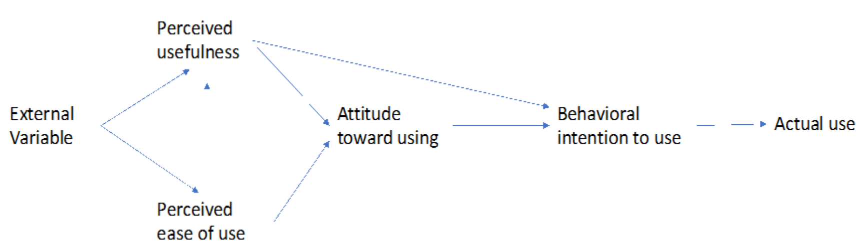

Fig. 2. A Technology Acceptance Model

The Technology Acceptance Model (TAM), based on the Theory of Reasoned Action, is comprised of beliefs such as perceived usefulness and perceived ease of use influencing attitudes toward use and behavioral intention to use which lead to acceptance of the technology and actualization of specific outcomes (Davis et al., 1989; Turner et al., 2010). TAM in Figure 2 is a scientifically supported model in the information technology field. This theoretical model has been utilized to explain utilization, adoption, and user performance of new technology in a myriad of disciplines. In the arena of healthcare and medicine, TAM has been used to describe the intention to use in all manner of innovative technology to improve health and healthcare delivery and has provided explanatory power for actual use. The theory is the gold standard in industries outside health care and accounts for 30-40% of IT acceptance (Holden & Karsh, 2010; Legris et al., 2003). TAM, however, is very restrictive in studying the behavioral intention to use and often fails to account for the total variation in actual use. Again, the study design has to incorporate a multi-wave or longitudinal study design in order to demonstrate its viability for predicting use or outcomes of TAM.

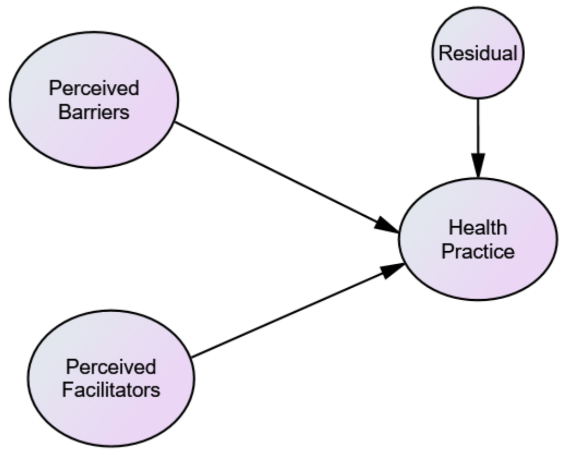

Fig. 3. A Health Beliefs Model

The Health Belief Model (HBM) was developed by Rosenstock and Becker in early 70' to identify potential barriers and facilitators for preventive health practice. HBM is composed of five main constructs: perceived susceptibility (perception of the possibility of experiencing a condition that would adversely affect one's health), perceived severity/seriousness/threat (perception of the negative effects of a condition (i.e., pain, discomfort, death, etc.), perceived benefits/facilitators (belief of the availability and effectiveness of an action) to taking action and perceived barriers (belief for not taking action because of inconvenient, unpleasant, expensive, etc.) to taking action. These constructs are applied to the individual's cues to action. Cues to action can be internal (i.e., perception of bodily state) or external (i.e., interpersonal interactions, the impact of media communication, receiving communication from a doctor) (Rosenstock, 1966; Rosenstock et al., 1988). HBM has been applied to a broad range of health behaviors and subject populations and extensive psychometric development and assessment of measurement tools for the theoretical constructs have been observed in the literature. Most notably, HBM is applied to preventive health behaviors (i.e., addressing health promoting and health risk behaviors), sick role behaviors (i.e., compliance with recommended medical regimens), and in clinic use (Rosenstock, 1966). Figure 3 abbreviates the constructs to demonstrate the effect of perceived benefits and barriers on health practice. However, HBM has yet to incorporate external forces such as the contextual environment, market, culture, and political system that may directly or indirectly influence the behavioral practice or outcome as the endpoint in health evaluation studies.

Noting that the three aforementioned theoretical frameworks popular for HIT evaluation have their limitations, we propose a transdisciplinary framework (Gurupur et al., 2016) as a newly emerging approach. The HIT-Use Outcome model provides support for the contextual/ecological factors as well as technology use. TAM provides support for technology use, and HBM provides support for personal and behavioral factors. Thus, the framework integrates contextual/ecological and personal and behavioral factors as predictors of HIT use and health practice which could be designed and used for health services evaluation (Figure 4). It may call for a design of a multi-level model for HIT performance research. This model enables to include main predictors and their interaction terms as moderating factors. Sections 3 through 5 of this article describe the processes to design, validate and implement the framework, respectively. Table 1 in Section 5 exemplifies each of the constructs in Figure 4.

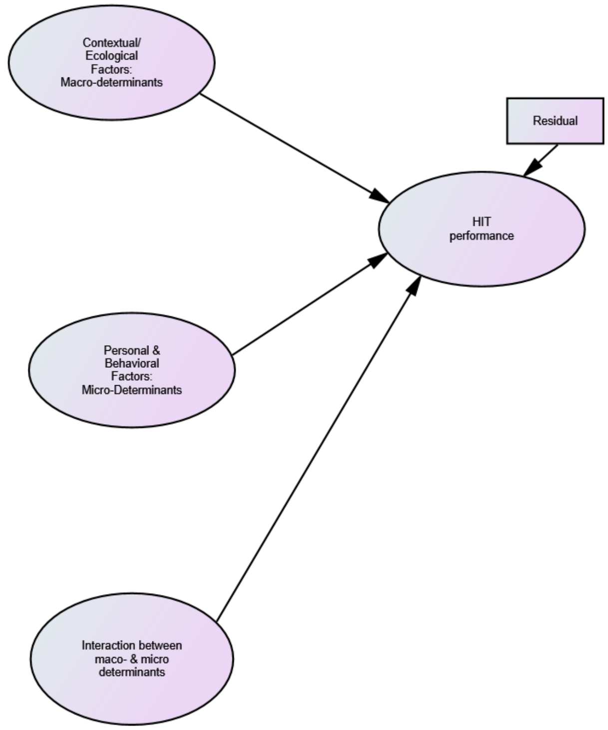

Fig. 4. A Transdisciplinary Approach to HIT Performance/Outcomes

3. An Evidence-Based System Approach to Evaluation: A Logic Model and Its Design

Here it is important to mention that a generic logic model was first developed by agricultural extension researchers for diffusion and innovation studies (Joly et al., 2007; Knowlton & Phillips, 2012). Logic models are a visual display of the pathway from actions to results and assume recursive relationships of three basic system components: Inputs, thruputs/outputs, and outcomes (Figure 5). Inputs are the resources used by the program and are identified by asking the question "What we invest" (e.g., money, supplies, staff, and ideas). Thruputs/outputs are the direct products of the program activities (e.g., the number of clients served, HIT use) which has the subcomponents of activities (the services the program provides or the work that is performed) and participation identified by asking "What we do" and "Whom we reach", respectively. The outcomes are the benefits resulting from the program activities (e.g., improved health, new knowledge, better skills, etc.), which are identified by asking "What are the results or impacts". Outcomes can occur at different levels measured at the individual, group, organization, or community level (Knowlton & Phillips, 2012). The model presented in Figure 5 shows outcomes observed in the short-term, medium-term, and long-term basis.

For health services management evaluation and research, five components of a logic model are specified in a recursive or causal chain model as follows: Input -> Activity -> Output -> Outcomes -> Impact. The model includes prescriptive (what actions are taken to produce the desirable outcome) and descriptive (causal processes expected to attain the goal) assumptions related to causal processes and relationships. For illustrative purpose, we detail the contents for each component for the design of HIT research as follows:

Input. A framework for integrating databases derived from electronic health records (EHRs) and assessment for coordinated polychronic care; resource development; stakeholder, leadership and participation; and scientific review of action plans.

Activity. A shared vision of coordinated polychronic care with health information exchange or digital health applications; information sharing and development; design and assessment of interoperability of inpatient and ambulatory care data system and work plan development; service gap analysis; communication and reporting system; service-line management; process redesign and consultations;

outcome tracking tools and procedures developed for each intervention (e.g., HealthyTutor, simulated learning, coordinated polychronic care); performance measures; and comparative effectiveness analysis plan.

Output. Value-added information exchange training and simulated learning activities for providers instituted; use of health technology for improving knowledge, motivations, attitudes, and practice in polychronic and preventive care; care process redesign and transformation; the number of patients referred and served; the number of consultations provided to clinicians; guided care implementation and assessment; changes in practice to reflect value chains; the number of coordinated care units established throughout the community; and activities and accomplishments documented and reported.

Outcomes. Proximal outcomes in terms of satisfaction with care and improved use of HIE and personal health record (PHR) technologies; increased collaboration in the implementation and coordinated care for polychronic conditions; reduced hospitalization and institutionalization of elderly patients in the community; better patient outcomes; improved communication and coordination among social and health organizations; and work-forces retraining and health exchange related to job creation in the community.

Impact. Reduction of sentinel health events; improved population health; improved preventive practice in dealing with polychronic conditions such as diabetes, heart disease, cancer, stroke, etc.; reduced wasteful and duplicated tests or lab work; improved efficiency in the delivery of polychronic care; and enhanced sustainability in the provision of coordinated care for polychronic conditions. The multi-criteria optimization in the evaluation enables investigators to effectively assess the impacts of the intervention program.

The development of the HIT-based logic model allows stakeholders and evaluators to visually identify major components and indicators as well as plan and communicate goals and resources needed within their HIT research. The causal assumptions specified for the evaluation components have to be validated to confirm the proposed model, using structural equation modeling (SEM).

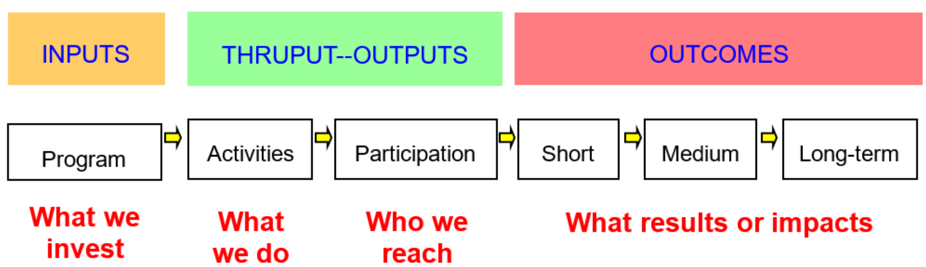

Fig. 5. A Logic Model for Research

4. Methodological Rigor in Validating Conceptual or Theoretical Models

The theoretical framework selected by the investigator enables 1) the development of measurements of study variables and 2) the specification and identification of parameters needed to examine the goodness of fit of a theoretical model in SEM, irrespective of the discipline (Wan, 2002). Hypotheses of the structural relationships of an endogenous variable (consequence, result, or outcome) to its exogenous predictive (latent or non-latent) variables could be specified by the theoretical model in performing systems analysis. It is an ideal analytical technique as it allows for multiple causal paths to be modeled in one analysis. Currently, a variety of software for SEM are readily available for use, such as LISREL, AMOS, STREAMS, Mplus, Smart- PLS3 (Ringle et al., 2005), etc.

Before the validation, it is highly recommended that stringent validation criteria be formulated before the evaluation or assessment of a theoretical model is conducted. This will require healthcare organizations to design and implement strategies for mitigating external threats and HIT for the application to polychronic conditions. Ultimately, a parsimonious and predictive model may emerge from SEM (a covariance-based analysis of normally distributed variables) or partial least squares modeling (a variance-based analysis for theory exploration and enhancement of R-squared value for the outcome variable).

5. Proactive Healthcare Technology Strategies for Mitigating External Threats

Healthcare organizations must develop proactive HIT strategies for mitigating external threats such as the COVID-19 pandemic. As a complex organization, healthcare systems are adaptive to the environmental change as well as responsive to the demand for coordinated and integrated care for chronic conditions. One feasible HIT strategy is to prepare and install a flexible infrastructure that is innovative and disruptive to the silos through the development of collaborative and cooperative data-sharing agreements among clinicians and providers in all levels of care. Thus, HIT strategic plans are not just developed and instituted for handling medical disasters or crisis events. The stability, viability, resilience, and productivity of supply chains for chronic care of the healthcare system can then be maximized.

Recall that our proposed framework for the transdisciplinary approach to HIT performance is composed of three constructs: macro (contextual/ecological) and micro (personal/behavioral) and interaction of macro and micro factors. Table 1 summarizes the impacts of macro- and micro-level predictors for the performance of healthcare organizations in taking care of the chronically ill. Relevant HIT applications for polychronic conditions via big-data and meta analysis (Heerspink et al., 2019; Zhou et al., 2017), health cloud (Zhu et al., 2020), artificial intelligence (AI) (Kaul et al., 2020; Le Berre et al., 2020), geographic information system (GIS) (Turnbull et al., 2020), apps (Nouri et al., 2018; World health Organization, 2018), health smart (LeBaron et al., 2020), digital health and telemedicine (Andersen et al, 2018; Gurupur et al., 2017), graphic-user interface (GUI) (Yoo et al., 2020), RFID (Frykberg et al., 2011), health information exchange (HIE) (Kebede et al., 2019), personal health record (PHR) (Ikeda et al., 2018), electronic health records (EHRs) (Dalton-Locke et al., 2020; Wu et al., 2020), digital health application (DHA) (Dixon et al., 2019), IoT (Nam. 2019), health platform (Lee et al., 2013), etc. are cited in numerous reports as well as in Table 1.

Utilizing proactive strategies not only supports collaboration among healthcare organizations but also enables to facilitate interdisciplinary research while reducing inherent bias, improving population health management, suggesting the process of improving clinical health outcomes of polychronic condition patients through improved care coordination and patient engagement, and ultimately reducing the burden on the patient and the healthcare system.

6. Discussion on A Shared Vision and Collaboration Between HIT Industry and Academia

The industry-academic collaboration is a pivotal strategy for developing artificial intelligence and its applications to healthcare (Wan, 2020). Substantive contributions could be made by major stakeholders or partners. It is reported that among 650 IT tools have been developed for enhancing clinical decision support, diagnostics, predictive analytics, and clinical integration (www.startus-insights.com). For instance, the RAMP Medical offers alerts and reminders, the Medical Algorithms Company enables the documentation, the Cohesic is a workflow tool, and the Tapa Healthcare offers disease-specific decision support systems.

In light of the current developments in the HIT industry, notable accomplishments have been realized in several areas of polychronic care, such as the Care Centrix for post-acute care management to power clinical decisions, the Masimo to produce health instruments or devices enabling the delivery of home care, the Objective Medical Systems to provide physicians to remotely monitor patients with heart conditions with clinical workflow and analytics for improving interactions between providers and patients, the GoMo Health to establish the personal concierge for behavioral health and treatment, the Lexis Nexis for risk identification and solutions, and the C3 Cloud with the semi-automatic care plan design and implementation for individualized care in Euro-countries (Laleci Erturkmen et al., 2019). Further advancements in decision support models, employing population health management strategies, are needed to improve early identification and risk stratification of targeted patients, care management programs and delivery through effective utilization management and quality improvement, and patient engagement management activities for the population with polychronic conditions. In addition, the application of machine and deep learning techniques to chronic disease management holds a very promising role in the AI development for population health management.

Table. 1. The Impacts of Macrio- and Micro-Level Predictors for the Performance of Healthcare Organizations for the Chronically Ill

Macro- and Micro-Level Predctors	Typology of Healthcare Organizational	Proactive HIT Strategies for Polychronic Conditions	Evidence of HIT Application for Polychronic Conditions
Macro-Level Contextual/Ecological factors	WHO Government Insurance company Industry	Identify High-Risk Population for Polychronic Conditions Selecting Target Conditions by Conducting Systematic and Meta Analysis Standardizing the Measurement Tools for Process and Outcome Sharing and Analyzing Big Data to Develop and Validate Predictive Models Leveraging Health Policy and Patient Centric Management Strategies	Big Data Health Cloud AI GIS APP
Micro-Level Personal/Behavioral Factors	Patients Healthcare providers Researchers	Developing Graphic-User Interface (GUI) for Enhancing Self- Care Conducting Randomized Clinical Trials	GUI Device AR/VR RFID HIE PHR/EHRs DHA
Interaction between Macro/Micro Level	Stakeholder Partners Platform	Establishing a collaborative platform Simulating Theoretically Sound and Empirically Validated Decision Support Models	Health Smart Platform eHealth IoT

HC: Health Cloud
GIS: Geographic Information System
GUI: Graphic-User Interface
HIE: Health Information Exchange
EHRs: Electronic Health Records
AI: Artificial Intelligence
APP: Application
RFID: Radio Frequency IDentification
PHR: Personal Health Record
DHA: Digital Health Application

Following is a short list of feasible and promising avenues for collaboration in leveraging and optimizing personal and population health management of polychronic conditions:

1) Identify High-Risk Population with Polychronic Conditions: The efficiency of predictive analytics for disease management could be achieved if the high-risk population is identified and incorporated into intervention design and evaluation. For instance, clinicians and population health scientists could identify a high-risk group for diabetes II patients who are not adhering medications or medical regimens. Interestingly enough, we also know that preventive practice and outcomes (O) are affected by the knowledge (K), motivation (M), attitude (A) and practice (P), the KMAP-O model for improving better diabetes care and outcomes (Rav-Marathe et al., 2016; Wan et al., 2017).
2) Selecting Target Conditions by Conducting Systematic Review and Meta-Analysis: Careful inspection of scientific journals and other publications reveals that systematic reviews and meta-analyses are frequently performed. Valuable information and insights have been gained from reviewing and synthesizing the published literature. However, most of them are limited to the assessment of clinical intervention effects, not much on the effects of human factors, such as choice (self-efficacy), restfulness, healing environment, activity, trust of providers, interrelationship, outlook or orientation, and nutrition. An example is also presented in a recent publication on heart failure hospitalization (Wan et al., 2017).

3) Establishing a collaborative platform for managing polychronic diseases: Digital healthcare is a fashionable mode for coordinating and integrating care for complex problems of patients suffering from polychronic conditions. The ability to formulate semantic interoperability of EHRs and PHRs via C3 Cloud system is desirable (Laleci Erturkmen et al., 2019).
4) Conducting Randomized Clinical Trials on Polychronic Care Management Innovations: A variety of care management strategies are noted. However, a limited number of randomized clinical trials of intervention strategies are being conducted. The payoff is relatively high if HIT industry is willing to support the design and implementation of care management strategies or innovations with guided theoretical frameworks (Wan, 2018a).
5) Standardizing the Measurement Tools for Polychronic Care Process and Outcome Measures: The psychometric properties of care process and outcome measures have to be examined and then standardized. For instance, the Euro-Qual 5-D instrument has been well recognized for its validity, reliability and applicability for assessing health and functional status of the chronic care population. Another example is related to pain measurement, particularly for the elderly. With a multi-wave or longitudinal study design, pain measurement research could be strengthened (Wan et al., 2019).
6) Sharing and Analyzing Meta Data or Big Data to Develop and Validate Predictive Models: The so-called Machine Learning and Deep Learning approaches to the evaluation of interventions for chronic conditions are critically needed. For example, we need to know and understand the trajectories of polychronic conditions through statistical modeling and simulation of factors influencing the initial state and the change trajectory of each chronic condition at the population level (Wan, 2018c). Both stationary and non-stationary Markov models could be explored in the development of parsimonious predictive models of chronic care outcomes.
7) Guiding the Development of Graphic-User Interface (GUI) for Enhancing Self- Care Management: It is essential that patient engagement protocols be designed and improved effectively. GUI-based software for self-care management is needed. For instance, web-based technology has been developed and implemented for reducing caregivers' burden and stress in the dementia population by the National Center for Creative Aging (Golden et al., 2017; Wan et al., 2016). Users have free access to this artistic tool with 15 modules via the website (see www.NCCA.org).
8) Simulating Theoretically Sound and Empirically Validated Decision Support Models: The development and application of user-friendly Internet-of-Thing (IoT) technologies may facilitate the improvement of polychronic care management and disease prevention (Wan, 2018c, 2020).
9) Leveraging Health Policy and Patient Centric Management Strategies: Given the competitive nature of medical market, health care financing for HIT development and adoption should consider cost efficiency into the evaluation of health care technology use, particularly related to polychronic conditions. The demand and supply of efficient and effective HIT tools or devices could drive the innovativeness of HIT performance. Thus, the efficiency-quality tradeoff relationship of HIT could be better ascertained from healthcare evaluation and research.

7. Concluding Remarks

This article offers an integrative social-behavioral system approach to the management of polychronic conditions. By reducing disciplinary silos and proactively incorporating a collaborative approach to polychronic conditions management with HIT strategies, we provide pathways to improve patient outcomes. It presents theoretically informed frameworks or models to guide HIT evaluation. In addition, it also highlights the innovativeness of employing multi-criteria optimization strategies for designing decision support systems for improving the effectiveness and efficiency of disease management for targeted subpopulations.

Patients with polychronic conditions typically have a persistent and possibly expanding the scope of HIT use through the end of their lives. The adaptability, viability, resilience and productivity of the healthcare supply-chain systems will continue to change in the pursuit of excellence in service quality (Ivanov & Dolgui, 2020). The patient-centered care management will play an essential role in promoting population health (Wan, 2018b). Our research supports leveraging behavioral components of predictive model for HIT use to improve management of polychronic conditions. We should solidify the synergy between the HIT industry and academic researchers as a pivotal ingredient for generating confirmative approaches to theory building and validation. We demonstrate that the flexibility of trimming or parsimonizing a complex model for predictive analytics is needed before one can venture into decision support design and application, particularly in health management and informatics research. With the collaboration generated by a sharing common vision among scientists, providers and the HIT industry, we can then find optimal solutions for solving health and social problems associated with polychronic conditions. The discussion and critical perceptions provided by the article are necessary for improving the processes associated with the design and evaluation of health information technologies. The authors hope that these contributions will be used by practitioners and researchers in the future to further elevate this area of research and its associated applications.

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