Research Article

A Population Health Approach to Care Management Interventions and Healthcare Artificial Intelligence

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Abstract

Aging is associated with a decline of physical and mental health capacities. Previous studies showed that the increase in health services use is directly related to the need for care manifested at the personal level. The purpose of this article is to highlight the importance to formulating a theoretically informed and empirically verifiable framework such as the behavioral systems model. The design of an effective care management intervention needs to apply multiple strategies assisted by health information technology and treatment plans for population health management (PHM). A guided care plan developed under this system framework offers opportunities to capture essential patient care data and to coordinate care management activities such as risk identification, care management, demand/utilization management, quality management, and patient engagement management. Thus, a coordinated effort in performing varying care management tasks or activities centered in patients enables them to achieve efficient and effective utilization of health and social services and maximize their outcomes of care. The use of decision support software and artificial intelligence techniques holds great promise to improve population health management and self-care processes.

Keywords: population health management, behavioral systems model, care management strategies, predictive analytics, logic model, and artificial intelligence in health care

Introduction

Population health is a collective performance of people or population residing in a defined geo-spatial area [1]. Health status is measured by both general population and patient population in multiple communities. The determinants of population health consist of multiple factors such as the predisposing, enabling, and need-for-care factors, and healthcare utilization variables. The causal specifications for this behavioral systems framework integrated with care management strategies are presented in Figure 1 [2].

The population and individual determinants of health care needs may include the predisposing (e.g., demographic characteristics, knowledge, motivation, attitudes, cultural norms, rural-urban residence, ecological environment, educational attainment, etc.) and the enabling factors (e.g., income, health resources, insurance coverage, access to primary care, medical ecology, health information and referral networks, etc.). These two major predictor factors are not independent to each other and may directly affect the variability in the need for care and, in turn, influence the variation in health services use. In addition, literature also suggests that the predisposing and enabling factors may also directly influence patient care outcomes [3-5]. These causal assumptions are imbedded with the behavioral systems model of health services use as follows:

1. Care management interventions are the practical application of multiple strategies assisted by health information technology and treatment plans for population health management (PHM) [1]. Initially, PHM employs risk classification or market segmentation as a risk management approach to identify mutually exclusive or homogenous subgroups of patient population in the community so that services or interventions could target the need for care under varying conditions. This targeting approach to risk management is then followed by additional two applications of population health management: 1) utilization/demand management; and 2) chronic disease management. Quality management will be applied in all three phases of PHM.
2. Patient care outcomes constitute the proximal (e.g., patient satisfaction), intermediate (self-report health or health-related quality of life), and distal (clinical indicators of health) outcomes [6,7]. Utilization variables or demand management may directly influence the variability in patient care outcomes and population health [1].

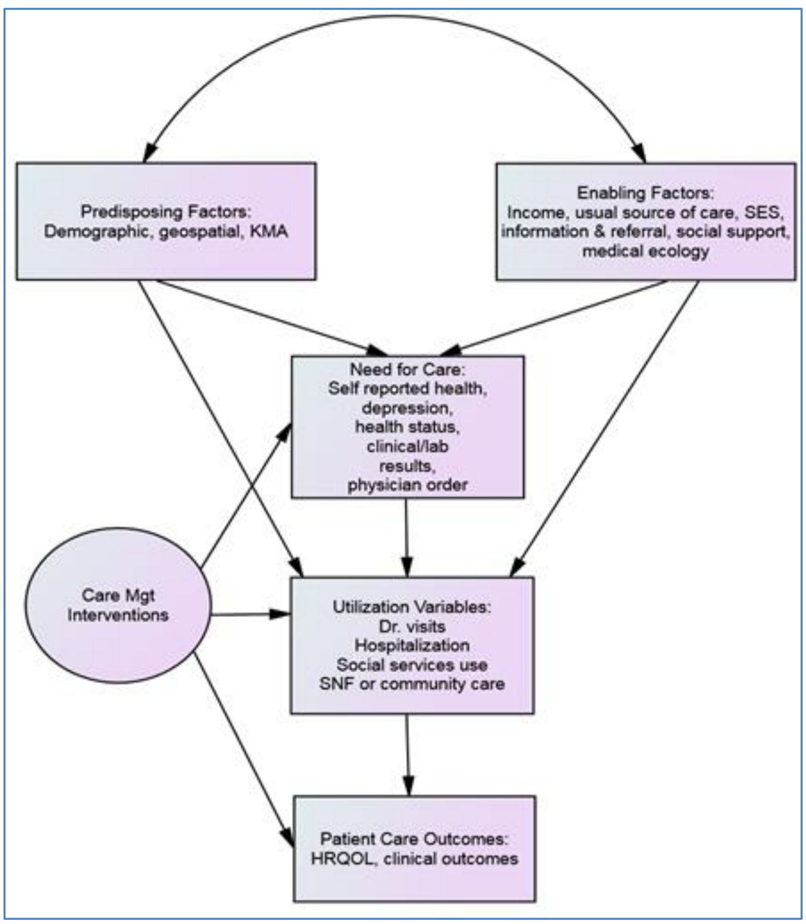

Figure 1: Design of care management interventions under an eco-bio-behavioral systems framework

Research Objective

The primary objective for this article is to develop managerial applications at varying levels or stages of PHM. The specific aims are derived from the theoretical framework presented in Figure 1.

Aim 1: Segmentation of the population at varying levels of the risk exposure to medical ecology and environmental threats by identifying relatively homogeneous subgroups of the population as the target for risk management and intervention design. Through this targeting approach to the needs of each subgroup, the delivery system can avoid the pitfall of employing a one-size-fits all approach. Thus, optimal outcomes and efficiency can be achieved.

Aim 2: Detection of relevant personal and societal factors influencing the variability in health and social services utilization to achieve utilization/demand management effectively.

Aim 3: Evaluation of care management interventions for quality improvement and their impacts on population health or patient care outcomes.

Aim 4: Identification of an optimal and significant number of predictors of population health so that a patient-centred care model can be established. Through simulation and simulated learning, this model can demonstrate the utility of guided care strategies to optimize self-care management, reduce hospital readmissions associated with poor quality of care, and contain high cost of care at the population level.

Aim 5: Illustration of how a theoretically informed behavioral systems model coupled with care management activities, specified in Figure 1, enables us to develop decision support products and artificial intelligence usable for enhancing the reduction and control of chronic conditions. Thus, evidence-based research on innovative m-health services or personalized care can be conducted [8].

Analytic Approaches to Achieve the Aims

Risk identification or population segmentation: Knowledge management advocates that effective and efficient use of big data enables users to understand the underlying sources of variations in an observed outcome or service utilization. The pattern detection or predictor tree analysis (Wan, 2002) is often used in segmentation of a population into relatively homogenous subgroups that reveal diversities in health needs or conditions amenable to health service interventions. This approach can be optimized when a cloud-based data warehouse is constructed and utilized by data scientist. The Community-based Epidemiological Study on Depression (CESD), developed by the National Center for Health Statistics, is to help assess the depression of a general population in a community [9]. The use of data generated from community surveys or assessments of patient care leads to the deployment of the big-data-to-knowledge (B2K) approach. Following is a list of data analytic tactics required for the B2K project:

Establishing data warehousing: The research files have to be constructed and then variables populated under theoretical constructs identified in Figure 1. Variables have to be recoded and imputed for some of the missing values under specifications for the predictor variables. New research and interaction variables are to be constructed if it is needed. For example, "depression" consists of 18 items as developed by the National Center for Health Statistics, that may reveal specific domains or constructs related to the state of depression of a population, namely in the psychological state (affect), somatic health, wellbeing and interpersonal relationships. The validity and reliability of such a depression scale has been systematically and empirically evaluated [8].

Variable construction: The scale based on multiple related items has to be evaluated by both exploratory and confirmatory factor analysis. For example, SF-36 consists of 36 items of health status measure [10,11]. Before the construction of physical- and mental- health status subscales, each item has to be examined and coded properly.

Missing values for some indicators or items could be imputed if missing for the item is completely randomly occurred and observed.

Codebook: A new data codebook has to be constructed. The codebooks serves as a map to trace the information and help to sort out the variables relevant to the study purpose.

Research design: Both cross-sectional and longitudinal models should be formulated, contingent upon the availability of the variables from the original data file.

Statistical analysis: Both descriptive and inferential statistics should be employed. For a multivariate model such as Figure 1, it is imperative to employ causal modeling techniques such as path analysis or other structural equation modeling techniques. In addition, the predictor tree analysis such as DTreg [12] could be used to identify mutually exclusive homogenous subgroups of the study population. With the availability of large datasets, one can not only develop a time-span (retrospective or prospective) study and also formulate a systematic evaluation of the reproducibility of data patterns recognized through machine learning or artificial intelligence techniques.

Detection of relevant predictors or factors influencing the variability in health and social services utilization

This major aim in designing predictive analytics is to capture the information to illustrate the causal sequela of multiple events or observed variables in an experimental or quasi-experimental study design. The analytical techniques for modeling used may vary by study design. The details on multivariate statistical modeling or multilevel modeling can be viewed from Wan's Evidence-Based Health Management: Multivariate Modeling Approaches [8]. The predictor variables may be classified into direct causal factors, moderating or mediating factors, and confounding factors.

Direct causal factors: In Figure 1, the need-for-care factors are direct causal factors for explaining the variability in service utilization. Thus, the need-for-care factors are viewed as having a prime or dominant influence on the variation in use of health or social services [13]

Intervening factors: The moderator is a factor modifying the relationship between the predictors and the observed outcome variable [14]. For instance, the availability of social support, either through instrumental support or expressive support, and the need-for-care may interact and exert an interaction effect on the utilization of health or social services.

The mediator or mediating factor exists if the causal specification of enabling factors exists between predisposing factors and service utilization. For instance, patients with poor knowledge, motivation and attitude toward wellness activities as the predisposing factors may have experienced an undesirable health outcome if primary care is not accessible or used. Thus, the availability of primary care mediates the relationship between the predisposing factors and the outcome variable.

Confounding factors: An extraneous or extra factor that may be miss-specified or ignored in the investigation is called a confounding variable or factor. The confounder may cause variability or bias if this variable is not properly adjusted or statistically controlled in the study. For example, the behavioral systems model has to consider the contextual variable such as rural-urban residence or other ecological/spatial factors in the investigation of variability in health services outcome. The lack of attention to ecological differences may misguide the development of an ineffective intervention.

Evaluation of care management interventions

The adequacy of care management strategies used may influence the variability in patient care outcomes. Previous research demonstrates that the presence or absence of a care management intervention alone may not directly influence patient care outcomes [13,15]. The lack of treatment integrity or fidelity may have explained the reason for failing to demonstrate the care management effect on the care for the chronically ill. In other words, most of chronic care studies fail to articulate the dose-response relationship between care management intensity and patient care outcomes. An alternative strategy is to formulate a case management intervention that can quantify the intensity (dosage) coupled with the duration of an intervention clearly. With the assisted technology available to capture data via telehealth or home monitoring device, heart patients can follow the guided care modality to avoid hospital readmission [16]. Evaluation research should undertake a thorough assessment of the structure-process-outcome aspects of the quality of intervention, as suggested by Donabedian [17].

The structural aspects of quality: The structure of a care management intervention can be viewed from staffing size and qualifications. For example, Wan et al. [18] investigated nursing staff adequacy and its effect on nursing home quality of residents. The inadequate staffing was viewed as one of the culprits of poor nursing home care.

The process aspect of quality: The design of a care management modality can be monitored during the implementation of service intervention. Evaluation should focus on activities or levels of care management process. A long-lasting effect of guided care for chronic conditions should capture the adherence levels, particularly in the evaluation of type-2 diabetes treatment and control.

The outcome aspects of quality: It is essential to collect relevant subjectively and objectively observed outcome indicators for type-2 diabetes [19]. For instance, researchers on diabetes or obesity should monitor A1C or other metabolic measures on a regular basis. In addition, self-reported health or functional capacity of the patients should be gathered as well since they are inversely related to metabolic metrics such as A1C, cholesterol, lipid levels, etc.

Identification of an optimal number of predictors of population health

Guided by a theoretically specified causal model such as the behavioral systems model presented in Figure 1, one can identify an optional number of predictors of personal and population health outcomes such as the proximal (e,g., satisfaction with care management), intermediate (e.g., adherence to regimen) and distal (e.g., health status or clinical health status) outcomes.

The use of logic model: The person-centered care can be evaluated by the logic model that specifies the relationships among the input, output, and outcome variables. An example of a logic model for person-centered care is show in Figure 2.

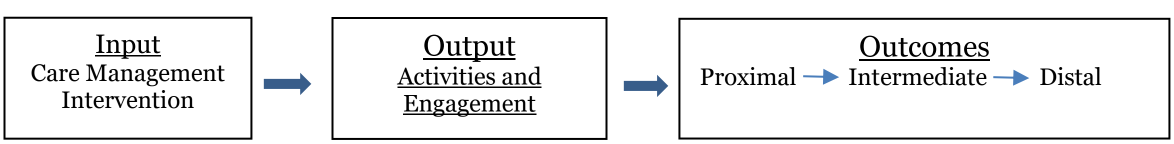

Figure 2: A Logic Model for Evaluation of Care Management Interventions

Development of decision support products and artificial intelligence usable for enhancing obesity reduction and control

Many commercial products for decision support are currently available to improve obesity reduction and control. However, the success of these products is contingent upon the effectiveness in monitoring and gathering consistent structure-process-outcome aspects of the quality indicators of guided care for chronic conditions. Several impediments are noted in the McKensey Medical Report on Artificial Intelligence and Machine Learning [20]. They include: the lack of awareness or education about AI, inadequate personnel or trained staff in AI, and limited use of a theoretically guided modeling approach to AI development. Most notable accomplishments in AI are related to tumor detection, diagnosis, and treatment by Watson Health [21] and the growth of AI applications in health care and robotic surgeries [22]. In health educational arena, Healthy Tutor, a software product developed by New MilllenniaHealth.COM [23] offers a comprehensive computer-assisted decision support for health behavioral changes or medical adherence. It follows a logically specified behavioral systems model (identifying a knowledge-motivation-attitude-practice-outcome framework) to solidify preventive strategies for reducing body weight, improving dietary change, and achieving glycemic control.

Implications and Concluding Remarks

This article highlights the importance of:1) translating experimental results from population health lab research to preventive measures and curative treatments for health disorders associated with obesity and glycemic disorders; 2) transforming big data into useable information and workable knowledge to improve care management strategies through the development of predictive analytics, artificial intelligence, and decision support products for managing population health problems such as chronic conditions; and 3) conducting transdisciplinary research on severe public health threats [24].

The prospects of achieving an optimal goal of population health are rested on the advancement of integration of theoretical knowledge and research methods in health care research by scientists from multiple disciplines in varying sectors in the globe. A dozen of primary care research inquiries on obesity and glycemic control, as an example for care management interventions, could be pursued as follows:

- Determinants of Health Care Needs of Obese and Overweight
- Individual and Societal Determinants of Health Services Use by the Obese and Overweighted
- Identifying a Population's Risk Profiles for Poor Health Status of the Obese
- Effectiveness of Care Management Interventions for Obesity
- Evidence of Chronic Disease Management Effectiveness in Obesity Reduction
- Care Optimization and Its Benefits at the Population Level for the Obese
- Decision Support Systems Design and Evaluation for Obesity
- Growth Curve Modeling of Patient Health Outcomes in Weight Control
- Ecology of Medical Care for Obesity

In conclusion, population health management strategies enable health professionals to target specific populations at risk for chronic conditions [24]. The care management interventions designed with the population health management principles can help maximize health benefits of the population when valid and effective decision support systems or artificial intelligence products are effectively utilized to improve self-care management and person-centered health care.

References

1. Wan TTH (2018) Population Health Management for Poly Chronic Conditions: Evidence-Based Research Approaches. Springer, New York, USA.
2. Wan TTH (2017) Community-Based Preventive Interventions for Childhood Obesity: Design Strategies for Implementing a Population Health Management Program. J Hosp and Med Manage 3: 19.

3. Andersen R, Newman JF (1973) Societal and individual determinants of medical care utilization in the United States. Milbank Mem Fund Q Health Soc 51: 95-124.
4. Wan TH, Soifer SJ (1974) Determinants of physician utilization: a causal analysis. J Health Soc Behav 15: 100-108.
5. Wolinsky F (1978) Assessing the Effects of Predisposing, Enabling, and Illness-Morbidity Characteristics on Health Services Utilization. J Health Soc Behavior 19: 384-396.
6. Wan TTH, Rav-Marathe K, Marathe S (2016) A Systematic Review on the KAP-O Framework for Diabetes Education and Research. Med Res Archives 3: 1-22.
7. Wan TTH, Terry A, McKee B, Kattan W (2017) KMAP-O framework for care management research of patients with type 2 diabetes. World J Diabetes 8: 165-171.
8. Wan TTH (2002) Evidence Based Health Care Management: Multivariate Modeling Approaches. Boston: Kluwer Academic Publishers, The Netherlands.
9. Ensel W (1986) Measuring Depression: The CES-D Scale. Lin N, Dean A, Ensel W, editors. In: Social Support, Life Events and Depression. Academic Press, New York, USA.
10. Ware JE, Shherborne CD (1992) The MOS 36-Item Short -Form Health Survey (SF-36): I. Conceptual Framework and Item Selection. Med Care 30: 473-484.
11. McHorney CA, Ware JE Jr, Raczek AE (1993) The MOS 36-Item Short-Form Health Survey (SF-36): II. Psychometric and clinical tests of validity in measuring physical and mental health constructs. Med Care 31: 247-263.
12. WWW.DTreg.com. A software designed to handle predictor tree analysis and other advanced statistical analyses.
13. Wan TT (1989) The effect of managed care on health services use by dually eligible elders. Med Care 27: 983-1001.
14. Yeh SCJ, Yuan KS, Chen SHS, Lo YY, Chou HC, et al. (2016) The Moderating Effect of Leadership on the Relationship between Personality and Performance. J Nursing Management 24: 869-883.
15. Zhang NJ, Wan TTH, Rossiter LF, Murawski MM, Patel UB (2008) Evaluation of chronic disease management on outcomes and cost of care for Medicaid beneficiaries. Health Policy 86: 345-354.
16. Williams C, Wan TTH (2016) The Influence of Remote Monitoring on Clinical Decision Making: A Pilot Study. Home Health Care Management and Practice 28: 86-93.
17. Donabedian A (1980) The Definition of Quality and Approaches to Its Assessment. Health Administration Press, Ann Arbor, Michigan, USA.
18. Wan TTH, Breen GM, Zhang NJ, Unruh L (2010) Improving the Quality of Care in Nursing Homes: An Evidence-Based Approach. Baltimore: Johns Hopkins University, USA pp: 109-110.
19. Ravmarathe K, Wan TTH, Marathe S (2016) The Effect of Health Education on Clinical and Self-reported Outcomes of Diabetes in a Medical Practice. J Integrated Design and Process Sci 20: 45-63.
20. Marr B (2017) The Amazing Ways How Artificial Intelligence and Machine Learning is Used in Health Care. Forbes, October 9.
21. Mukheijee S (2016) IBM Workers to use Watson Supercomputer to Find Cancer Treatments.
22. Research and Market (2017) Global Artificial Intelligence Market in Healthcare Sector: Analysis and Forecasts, 2017-2025 (Focus on Real-Time Monitoring, Precision Medicine, Personal Health & Nursing Assistants and Robot-Assisted Surgery).

23. NewMillenniahealth.Com (2017) Healthy Tutor is a health educational software to assess the participant's knowledge, attitude, preventive practice and outcomes of diabetes care and control.
24. Wan TTH (2017) A Transdsiciplinary Approach to Healthcare Informatics Research: Implications for Poly Chronic Conditions. J Health Inform Manage 1: 1-7.