Predictive Analytics for the KMAP-O Model in Design and Evaluation of Diabetes Care Management Research

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Abstract

This is a commentary on methodological challenges and analytical requirements in designing an evaluation of the knowledge, motivation, attitude, preventive practice-outcome (KMAP-O) model for selfcare management of diabetes. Critical issues pertaining to an investigation of the dose-response relationship between the intervention program and outcomes, the comparative effectiveness evaluation, and the lengths of observation were noted. Although numerous publications on factors influencing diabetes care and control were systematically reviewed and documented in the literature, scientific results on artificial intelligence research remain to be uncovered. To optimizing the knowledge and clinical practice in selfcare management, specific methodological approaches to predictive analytics are suggested for future clinical studies, using a comprehensive behavioral system such as the KMAP-O model.

Keywords

behavioral components of selfcare intervention, comparative effectiveness evaluation, AI research in diabetes care and control, predictive analytics, and methods

Important Behavioral System Components for Diabetes Care Research

A successful health education intervention for patients with diabetes and comorbidities requires a randomized controlled study design to detect synergistic effects of the knowledge (K), motivation (M), and attitude (A) of patients with diabetes on preventive practice (P) and outcomes (O) to enhance self-efficacy and patient centered care.[1,2] The causal imperatives for launching a thorough investigation of any interventions involved with lifestyle and behavioral changes should be better identified and considered in the design and evaluation of an intervention.[3]

In the past decades, many clinical experimental studies pertaining to diabetes care were concerned with the main effects of multiple components of diabetes care intervention while only a few published articles considered the synergistic and interaction effects of KMAP on care outcomes.[4] The intervention studies were relatively heterogeneous in their design while diabetes education usually consisted of goal setting, knowledge acquisition, individualized care and frequent follow up. Most of these studies measured the short-term outcomes through monitoring patients' adherence to medications, achieving

lower HBA1C, improving dietary control behaviors, and weight loss. Furthermore, most of the diabetes education studies showed statistically significant positive results in changing patients' behaviors and improving their health outcomes. However, it is unclear if the beneficial effect of diabetes education on outcomes of care is solely attributable to the components such as knowledge enhancement and coaching, motivational interviewing, attitudinal change, and preventive practice change. The annotated research summary of selected randomized trials has been detailed in previous publications.[5,6]

Findings show that behavioral interventions targeting the knowledge-motivation-attitude (KMA) components concomitantly had a greater impact on preventive practice such as

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exercise, dietary control, and regular physician visits than on improved metabolic and clinical outcomes. In addition, targeting specific high-risk patients who experienced a poor adherence could yield better outcomes.[7,8] The complexity involved in designing a patient-centered care management for type 2 diabetes is also well documented. The challenges may include the development of valid and reliable measurement instruments for the KMAP,[1] the formulation and implementation of a long-term rather than a short-term observation period,[9,10] the avoidance of biases,[11] and the appropriate application of predictive analytics for teasing out the causal sequence of KMAP.[8] To facilitate more consistent preventive practice and better outcomes, it is imperative to understand causal mechanisms leading to behavioral changes and other patient care outcomes.[1]

A few highly related methodological issues were discussed in the literature and needed more thoroughly reviewed to draw any solid conclusions. First, it is unclear about the length of intervention required. Although as many studies considered <6-month intervention is as short and >6-month interval is as long.[10] Appropriate lengths of intervention effectiveness for varying patient populations need to define such that the dose-response relationship between behavioral interventions and diabetes care outcomes could be ascertained. Furthermore, a wide spectrum of factors has yet to be considered in the formulation of a short-duration versus a long-duration assessment of the intervention program.[10,11] Second, the literature has not addressed the sequence of implementing program components. Furthermore, it is unclear if KMA components should be concomitantly executed to optimize better patient care outcomes. In other words, the causal sequence of KMA should be examined and ascertained in empirical studies. Third, the lack of consistent guidance is problematic regarding targeting patients or segmenting a diverse patient population who could specifically benefit from personalized or individualized interventions. The so-called targeting a group for specific interventions requires the consideration of contextual and ecological variations. Thus, it is suggested that the risk factors be thoroughly confirmed in both theoretical and methodological examination.[3]

In summary, future research on patient-centered care studies, employing the KMAP-O model, should explore the following options in conducting a scientific implementation science project:

1. Use both experimental and quasi-experimental study designs: Ideally, a randomized controlled study design is preferred. However, in a population-based study, it is feasible and reasonable to employ a propensity score matching and analytical approach so that the experimental or intervention group is comparable to the comparison group. Thus, the integrity of the experimental results can be ensured.
2. Define behavioral components of interventions: The adoption of innovation or new preventive practice behavior in disease management should be on par with the technology adoption model (TAM) such that a patient's perceived ease

of use or usefulness are queried as variables of acceptance. Both patient's reported outcomes and clinical outcomes should be carefully captured in the data collection for varying stages of the disease management process. Most importantly, the program should garner greater attention to personalized or individualized care management activities performed by trained coaches and motivators.

3. Use of incentives for facilitating adherence: Financial or other incentives could be properly used to incentivize the participants in the intervention study. However, the literature is unclear about the type and number of incentives that should be provided.[5]
4. Consider the use of health information technology (HIT): The design of a cloud-based data system may facilitate the adherence and compile relevant process and outcome indicators during the study period. Currently, numerous HIT based and commercially implemented diabetes education modalities are available for patients. For instance, the HealthyTutor.Com has a useful product for introducing appropriate knowledge, attitude, and preventive health practice for diabetes and hypertension.[12] If this product can also include motivating and coaching strategies to assist the patients or providers, it will certainly optimize the power of interventions for effective care management of diabetes.
5. Design valid and reliable measurements of KMAP components of the behavioral system: Although a variety of measurement instruments have been developed and used in diabetes education research, future research should be designed to demonstrate psychometric properties of the theoretical constructs (i.e., changes in knowledge, motivation, attitude, and preventive practice). The currently available measurement instruments could be further improved in their scale constructions. For example, the Likert-scale approach is popular and useful. It is highly recommended that the analog scale, ranging from 0 to 100 points, could be applied in the scale construction. Thus, the gradients or intensities of the knowledge, motivation, attitude, and health behavioral practice could be better portrayed by the measurement scales.[13]

Predictive Analytics and Applications to Diabetes Self Care Management

The KMAP-O model relies on the theoretical specification of behavioral system components. Each component constitutes multi-dimensional constructs or domains.[14] Carefully formulated measurements for each component of the KMAP-O model are suggested as follows:

1. The Knowledge (K) Component: Diabetes education is designed to improve the knowledge about etiologies, disease processes, therapeutic information, preventability, etc. It is expected that the knowledge enhancement could build the foundation for competencies. It is desirable to

formulate multiple levels of the assessment tool that can delineate the progression of the knowledge advancement. In addition, the competency assessment and measurement must be standardized and validated.

2. The Motivation (M) Component: There are numerous barriers for achieving optimal adherence to medication and prescribed behavioral changes. Both subjective (e.g., intent to act) and objective (e.g., willingness to do) aspects of motivation must be specified in the measurement. The use of boosters or computer-based reminders for solidifying the motivation to change could be explored.

3. The Attitude (A) Component: The attitude consists of 3 related sub-components, namely cognition/awareness, affect/valuation, and propensity to act. It is believed that a positive attitude change leads to a favorable behavior change. In other words, attitude is reflected by the 3 specific subcomponents (the first-order constructs serving as 3 related variables) to reflect an attitudinal construct.

4. The Preventive Practice Component: The preventive orientation forms the basis for preventive practice such as regular exercise, dietary control, stress management, medication use, physician visit, etc.

5. The Outcome (O) Component: Both self-reported outcomes and clinical outcomes are the essential part of therapeutic outcomes.[15] Because outcome indicators are positively related to each other, it is imperative to form an outcome assessment tool that consists of both self-reported health and clinically assessed outcomes, such as the A1C level and physical functional status.

It is desirable to develop highly valid, reliable, and applicable measurement instruments for assessing the effects of KMAP on outcomes. Though the advanced statistical modeling techniques is available, researchers prefer to employ the variance-based approach over the covariance-based approach to causal analysis by employing a Partial Least Squares (PLS) software (i.e., SMART PLS3). PLS via the use of software such as PLS3 overcomes methodological issues associated with a covariance-based program such as AMOS for assessing the measurement integrity of the instrument.[16,17] Through using the confirmatory approach, theoretical constructs could be validated and then generate systematical knowledge about the integrity of a measurement instrument for the KMAP-O model. Structural equation modeling may then be used to demonstrate causal sequences and mechanisms for behavioral and outcome changes regarding the KMAP-O model. For example, the predictive model of diabetes education success (improved outcome) is a joint function of K, M, A, P, and their interaction terms. In addition, the predictive model should include both time-varying and time-constant predictors into the model in a multi-wave study design.[13]

The ultimate solutions for deployment, integration, and visualization of multi-wave data have to be developed and implemented in a serverless environment so that the artificial intelligence (AI) applications for diabetes education research could be established at the large scale without data storage concerns and technical limits of a modern information system. Those who are technically oriented could examine the AI potentials for enhancing the performance of predictive analytics.[18-20]

The preventive disease management and health promotion activities, using AI products, have potential to generate a synergistic effect of KMAP-O components on diabetes care. The future development of AI applications is highly feasible by employing the KMAP-O model to evaluate and monitor the efficacy on varying population types and distinguish between behavioral outcomes and overall clinical diabetes outcomes. A key premise with a population health management approach[8,21] is to help health managers perform risk stratification and identification of those "at-risk" for poor adherence and outcomes (i.e., a high-risk patient group). However, this approach has always over-generalized the effect of an intervention program for its therapeutic outcomes. A more focused and personalized design for coaching and motivating behavioral change is needed to delineate a complex set of predictor variables that exist within cognitive to metabolic changes through a multi-criterion optimization technique. One of the greatest applications of DiabetesTutor will be to act as a decision support tool and assist an existing health consumer management regimen as a baseline and monitoring technology that is one component of a program that integrates additional tools for motivation and coaching. That is, by evaluating the performance of the patient on the outset of disease management, and again at intervals of knowledge deterioration, we can determine if the patient engaged in the study has a barrier to specific knowledge and behavioral change, while ensuring that additional coaching resources are efficiently used to bring the overall improved performance of patient-centric care outcomes. Similarly, we should also be able to expand a continuous improvement effort with a theoretical based implementation strategy.[22,23]

Conclusion

This commentary has briefly presented important components of a behavioral change model for patient-centric care. Specific conceptual and methodological issues are clarified, coupled with suggestions for improving diabetes education research. Future health research with artificial intelligence applications should carefully address the intensity or dose-response relationship between intervention components and outcomes. The KMAP-O model or other transdisciplinary oriented research[21,24,25] could serve as one of the heuristic frameworks for developing a longitudinal and multi-wave causal study and help advance the state of implementation science in diabetes education research with self-care management. The role of AI applications to digital health can be affirmed by the data-driving and empirically verified evaluation.

Declaration of Conflicting Interests

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