Behavioral Predictive Analytics towards Personalization for Self-management

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Keywords: Self-health Management, Behavioral Predictive Analytics.

Abstract: The objective of this research is to investigate the feasibility of applying behavioral predictive analytics to optimize diabetes self-management. In the U.S., less than 25% of patients actively engage in self-management even though self-management has been reported to associate with improved health outcomes and reduced healthcare costs. The proposed behavioral predictive analytics relies on manifold clustering to derive non-linear clusters. These clusters are characterized by behavior readiness patterns for subpopulation segmentation. For each subpopulation, an individualized auto-regression model and a population-based model are developed to support self-management personalization in three areas: glucose self-monitoring, diet management, and exercise. The goal is to predict personalized activities that are most likely to achieve optimal engagement. This paper reports the result of manifold clusters based on 148 subjects with type 2 diabetes, and shows the preliminary result of personalization for 22 subjects under different scenarios.

1 INTRODUCTION

Type 2 (Pre-)Diabetes is a chronic disease that affects over 115 million Americans and over 440 million people world-wide. Some of the risk factors are mitigatable or even reversible through behavior change towards a healthy lifestyle. It has been demonstrated elsewhere (Bollyky, 2018) that behavior change can achieve a 10% or more improvement in diabetes symptoms if an individual is engaged in proactive self-management of diabetes.

Self-management is generally accepted as a viable intervention strategy (Hadjiconstantinou, 2020). Self-management is the patient's ability to manage their chronic disease through their own activities, such as taking their blood glucose and focusing on meeting diet and activity goals. However, we do not fully understand the relationship between the behavior readiness of an individual and the specific intervention strategy that could deliver optimal patient engagement in self-management activities. As evidenced in a survey conducted elsewhere (Volpp, 2016), less than 25% of patients are considered as actively engaged in self-health management. Population health management will not be cost effective if self-management programs do not consider the readiness of the patient population. A contribution of this research is to provide an insight into the technical feasibility of behavioral predictive analytics. The goal is to optimize the effectiveness of self-management strategies by means of personalization based on predicting behavior readiness and its relationship to engagement outcomes. In this study, we aim to demonstrate a potential predictive system that delivers personalized content to the users based on their behavior readiness and user profile.

Section 2 contains a brief review on the state-of-the-art, and the context of this research within it. We will first discuss the Theory of Planned Behavior, and the use of behavior constructs as an attribute vector of behavior readiness. In section 3 the research results reported elsewhere will be restated as it is applied for in this research. In section 4 we will discuss predictive analytics for personalization using either an auto-regression model, or a population-based model. The population-based model provides a fallback mechanism when the auto-regression model derivation fails. This could occur when there is

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Sy, B., Chen, J., Beiting-Parrish, M. and Brown, C.
Behavioral Predictive Analytics towards Personalization for Self-management.
DOI: 10.5220/0010231801110121
In *Proceedings of the 14th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2021) - Volume 5: HEALTHINF*, pages 111-121
ISBN: 978-989-758-490-9

insufficient data, or it fails the statistics test of the model selection process based on Bayesian/Akaike Information Criteria. In section 5 we will present the results of manifold clustering based on the attribute vector of behavior readiness of 148 subjects with type 2 diabetes. This will be followed by the results of a preliminary study involving 22 subjects who were in the intervention phase for personalization during the study period. We will then summarize the results of this paper, discuss the limitations, and conclude with our future research plans.

2 RELATIONSHIP TO STATE-OF-THE-ART

The Theory of Planned Behavior is a popular theoretical framework in health psychology. It is used to describe the underlying psychological mechanisms that lead to changes in behavior. Within this framework, the individual has many beliefs about their behavior as well as beliefs about the normative behaviors expected within a social context. These all work together or in opposition to fuel behavioral attitudes and beliefs in subjective norms, based on the importance the individual places on these attitudes and norms. This then decides the individual's intentions which lead to the behaviors in question (Kan, 2017). In line with this theory, our research proposes targeting a user's behavioral beliefs to change their attitudes and intentions toward actionable health behaviors.

One of the most important features of our approach is the use of frequent reminders to track health activities that reveal information about appropriate health behaviors. In a review of the literature, Fry and Neff (Neff & Fry, 2009) found that frequent periodic prompts around: improving diet, increasing physical activity, and weight loss all led to positive results for study participants. Tailored prompts were especially found to be statistically significant in encouraging user engagement; however, for users who are already not engaged, these prompts do little to engage users (Bidargaddi, Pituch, Maaieh, Short, & Strecher, 2018). Sawesi et al. (2016) found in a systematic review of the literature that digital methods such as text messages, web applications, and social media interventions all were good intervention tools. These tools can support behavioral change in users and usually improve patient engagement. Finally, the use of mobile health interventions has been found to be an engaging method for improving health behaviors and is cost effective for the behavioral change (Van Stee & Yang, 2020).

3 PREDICTIVE ANALYTICS FOUNDATION

SIPPA (Secure Information Processing with Privacy Assurance) predictive analytics relies on two foundational building blocks developed in research reported elsewhere (Sy, 2017, 2019). The workflow process for the application of the proposed predictive analytics consists of three stages. In stage 1, an individual responds to a survey instrument linked to a behavior model for measuring readiness. In stage 2, the outcome measure of the behavior readiness determines the cluster/subpopulation that the individual is assigned to. The assignment is based on the similarity between the individual's behavior pattern and the statistically significant association patterns that characterize the cluster/subpopulation. In stage 3, the population based model and individualized week-over-week engagement models are applied to predict personalized weekly activities that optimize the success rate of engagement in self-health management. The details on stage 3 will be presented in the following section.

The first building block of SIPPA predictive analytics is a behavior model to enable behavior readiness prediction. Behavior readiness is a 1x4 vector of continuous (Real) numbers quantifying [*ownership, motivation, intention, attitudes*]. These behavior attributes of Real are constructs of behavior modelling grounded on the Theory of Planned Behavior. Structural Equation Modelling (Duncan, 1975) was employed to link questions of a survey instrument to the behavior constructs defined by a weighing factor derived from the confirmatory factor analysis. The behavior model linking to the survey questions were statistically validated based on the responses from over 500 participants (Sy, 2017).

The second building block is an unsupervised learning approach for discovering manifold clusters. The novelty of manifold clustering is to induce patient subpopulation clusters based on statistically significant association patterns. This approach is not restricted to only continuous data (number of Real). In other words, this approach could be applied to a data set of mixed-type of both continuous and discrete variables. A behavior pattern, which is manifested by the instantiation of finite discrete variables, is statistically significant if it survives two tests: (1) a support measure − as defined by normalized frequency occurrence − exceeds a pre-defined threshold according to the domain problem, and (2) the association among the observed values does not happen by chance as measured by the mutual information measure. There are two important results of the manifold clustering technique. First, each manifold cluster has a semantic interpretation characterized by statistically significant association patterns; i.e., grouping according to behavior readiness in this application. Second, the manifold clustering does not require linearity assumption as is in Principal Component Analysis (PCA). But it will produce the same result as PCA if the linearity assumption holds, and the iteration is based on minimizing reconstruction errors; i.e., "phase 2" regrouping is skipped in the manifold clustering. While the behaviour constructs are related according to the Theory of Planned Behavior, variations exist as shown in the confirmative factor analysis regarding the assumption on linearity; i.e., the existence (and strength) of a linear relationship between the behaviour constructs that quantifies behavior readiness for self-management in a population.

4 PREDICTIVE ANALYTICS FOR PERSONALIZATION

The *behavior* goal of personalization for self-management is to target specific user-directed activities that will be communicated to a user through a mobile app, and to inform "fulfilment" through feedback from the app. For example, when a personalized recommendation is to walk 10,000 steps a day, one would like to know whether a user follows through after the user received the recommendation from the mobile app. Two specific metrics are defined for this research to gain insights into the effectiveness of personalization:

Compliance Ratio (CR): Over a period of time, compliance ratio is the ratio of the number of times a proposed health related activity (i.e., actionable health) was acted on over the recommended/expected number of the related activity given the clinical condition/disease state of an individual.

Example: Over a period of 30 days, a diabetes user is encouraged to self-monitor one's glucose once a day under the clinical recommendation in commensurate to one's specific diabetic condition. The expected number of self-monitoring measurements is 30. Over this period the user self-monitors 18 times. Therefore, the compliance ratio is 0.6.

Engagement Ratio (ER): Over a given period, engagement ratio is defined as the total number of user interactions to the messages over the total number of messages sent. These messages are health tips or reminder for health actions, and are sent through text messaging, push notification, or as an in-app message.

Example: Over a period of 30 days, three messages are sent daily: one healthy tip, one reminder to self-monitor, and one reminder on exercise. The total number of messages sent is 90. A diabetes user responds to half of the healthy tips (i.e., 15 out of 30), and ⅕ of the reminders on self-monitoring, and ⅓ of the reminders on exercise. The engagement ratio is (15+6+10)/90 = 31/90.

4.1 Prediction based on Auto-regression and Maximum Likelihood

To facilitate the discussion on predictive analytics for personalization, let P be a population consisting of n individuals; i.e., $|P| = n$. $C = \{C1, \dots Ck\}$ is the set of subpopulations obtained by applying manifold clustering described in section 3 to P; where $Ci \subseteq P$, $Ci \cap Cj = \phi$ if $i \neq j$ and $P = \cup_i Ci$. p^j_{Ci} is the j^{th} individual in the subpopulation cluster Ci. Recall each manifold cluster Ci is characterized by one or more statistically significant association patterns of behavior readiness attribute vector(s). For each p^j_{Ci} individual, there exists a set of engagement/ compliance ratios over some period of time T. Let's denote the set of engagement ratios be $\{ER^1, \dots, ER^T\}$. T could be different from one individual to another due to the rolling basis of the enrollment into the pilot. For example, one individual who just starts self-management may have *(T=) 2* weekly engagement/ compliance ratios while another one in the same subpopulation may have *(T=) 6* weekly engagement/ compliance ratios. Yet they both belong to the same subpopulation because of their behavior readiness.

This proposed predictive analytics is based on a two-pronged approach. First, individualized auto-regression will be applied for personalization when there is "*sufficient*" data on the engagement (compliance) ratio on a type of messages related to self-management; e.g., healthy diet. Second, a population-based model prediction for personalization will be applied when an individual does not (yet) have "*sufficient*" data on the engagement (compliance) ratio, or the individualized auto-regression model derivation fails on statistic validation. There is *sufficient* data for generating an individualized auto-regression model when $T \geq 1$ for

l being the order of the auto-regression model as discovered through model selection criteria such as AIC (Akaike Information Criteria) or BIC (Bayesian Information Criteria) that pass statistical tests.

4.2 Information-Theoretic Model Selection Approach

Bayes and Akaike Information Criteria are two common information-theoretic approaches for model selection as stated below:

Bayes Information Criterion (BIC): $BIC(l) = ln(SSR(l)/T) + [(l+1)ln(T)]/T$ (1)

Akaike Information Criterion (AIC) $AIC(l) = ln(SSR(l)/T) + 2/T$ (2)

where l = number of lags,
T= total number of observations,
$SSR(l)$ = sum of squared residual calculated from the difference between the estimated value derived from l^{th} order auto-regression and the actual one.

Objective: choose l that minimizes *BIC/AIC* and $p\text{-}value < 0.05$, and R^2- correlation is "large."

4.3 Predictive Analytics for Personalization

Stage 1: The behavior readiness (a 1x4 vector of Real [*ownership, motivation, intention, attitude*]) of each individual in a population is derived based on the user's response to a survey instrument.

Stage 2: The population is partitioned into subpopulations based on the result of manifold clustering; where each cluster is a subpopulation. Further technical details about manifold clustering based on statistically significant association patterns could be found elsewhere (Sy, 2019).

Stage 3: Repeat the following for each possible self-management activity (e.g., self-monitoring, exercise, diet management):

For each subpopulation Ci, derive the population statistical (joint) distribution of ER and ΔER based on the available engagement ratios of all individuals ($p^j{}_{Ci}$) in the subpopulation; for $j = 1, 2, ... |Ci|$. In other words, the joint distribution characterized by $Pr(ER, \Delta ER)$ is derived from using the ER^t and ΔER^{t+1} $(t = 1 ... T\text{-}1)$ of each individual $p^j{}_{Ci}$ in the population who has participated in the study for a time period T. This is referred to as a <u>population-based model</u> to support predictive analytics specific to the subpopulation cluster Ci for the rest of the discussions in this paper.

For each individual $p^j{}_{Ci}$ residing in a subpopulation (manifold cluster) Ci:

1. Perform l^{th} order auto-regression (for $l = 1 .. k \leq T$) on successive change in engagement ratio ΔER; in other words, $\Delta ER^{t+1} = ER^{t+1} - ER^t$ where $t = 1 .. T\text{-}1$.

2. Perform *AIC* or *BIC* to determine the desirable lag l given the time series data that minimizes *AIC/BIC*.

3. Note the p-value and the correlation R^2 between the actual and the estimated based on some pre-selected threshold for R^2.

4. Predict the change in engagement ratio $\Delta ER^{T+1}{}_p$ based on auto-regression using $T, T\text{-}1, T\text{-}2 ... T\text{-}l$. If the test statistics in (3) are reasonable (i.e., $p\text{-}value < 0.05$ and $threshold \leq R^2$), keep the predicted value $\Delta ER^{T+1}{}_p$ and stop. Otherwise continue to step 5.

5. Determine the predicted value $\Delta ER^{T+1}{}_p$ based on $\Delta ER^{T+1}{}_p = \text{Arg}Max_{\Delta ER}\ Pr(\Delta ER|\ ER=ER^T{}_p)$.

Among the choices on the actionable health (e.g., self-monitoring, exercise, diet), determine the actionable health recommendation based on the one with the largest $\Delta ER^{T+1}{}_p$.

Predicting/recommending coaching agenda based on compliance ratio is similar by repeating the steps.

5 PRELIMINARY STUDY

The proposed approach was applied to the diabetes subjects of a self-health management pilot conducted under an IRB-approved study protocol (CUNY IRB #2018-1043). The objective was to investigate the impact of digital health solutions to affect individuals' behavior towards self-management of chronic diseases, particularly type 2 diabetes.

To be included in the study, the participants had to be at least 18 years old. They also needed a minimum education level of a high school diploma. An additional criterion was that the participants had to have an H1AC of 6.0, or a diagnosis of diabetes or pre-diabetes. This means that participants also had a perceived risk of developing or had already developed diabetes and other associated chronic illnesses.

The behavior model developed under previous research for predicting behavior readiness was based on a population of over 500 individuals. The population consisted of both healthy individuals as well as individuals with chronic diseases. The statistically validated model was applied in stage 1 of the proposed predictive analytics for personalization.

148 individuals with type 2 diabetes were involved in stage two of the preliminary study. These participants had a mean age of 49 and a mean H1AC

of 7.89%. The population characteristics are shown below:

Table 1: Participant Demographic Information.

Ethnicity:	**Distribution:**
Caucasian	41.40%
African American	30.90%
African American/Hispanic	3.10%
Asian	13.80%
Hispanic	7.50%
Hispanic/Caucasian	1.10%
Indian/Asian	1.10%
Mexican/Black	1.10%
Income (in U.S. $):	**Distribution:**
$0 - $24,999	27.50%
$25,000 - $49,000	23.33%
$50,000 - $99,999	28.33%
$100,000 - $150,000	12.50%
$150,000 - $199,999	4.17%
> $200,000	4.17%
Education level:	**Distribution:**
High school diploma	17.89%
Some college - no degree	21.95%
2-yr college degree	16.26%
4-yr college degree	26.83%
Some graduate work	5.69%
Graduate-level degree	11.38%
Self-perceived health	**Distribution:**
Poor	8.13%
Fair	28.46%
Good	43.09%
Very good	16.26%
Excellent	4.06%
Sex:	**Distribution:**
Female	51%
Male	49%

The survey responses of these 148 individuals were used to identify manifold clusters (subpopulations). Individuals were grouped into a cluster when their behavior readiness measures were close to the statistically significant association patterns characterizing the cluster. Four manifold clusters were obtained for stage 2 of this proposed approach.

Among the 148 individuals participating in this pilot on a rolling basis, some were still in a one-month hold period for establishing a baseline without intervention; i.e., they have not entered the pilot phase for personalized intervention. On the other hand, some others already completed the intervention phase of the pilot. Excluding these two groups, 49 subjects with type 2 diabetes were left to be included in deriving the population-based models for personalized intervention. These were the subjects who entered/were in the intervention phase of the study as of this report. The self-health management focused on the following three health coaching agenda items:

- Knowledge building and information gathering (through daily wisdom sent via SMS and/or push notifications)
- Discipline and skill development (through notifications and reminders)
- Awareness improvement (through weekly survey)

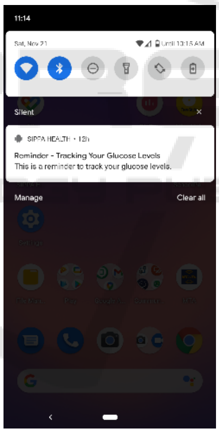

Figure 1: Push notification.

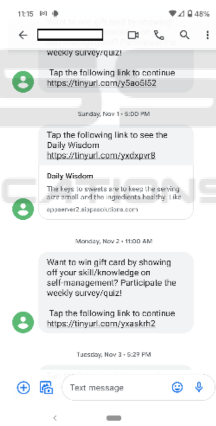

Figure 2: SMS reminder.

The self-health management activities of this pilot included the delivery of (1) daily wisdom on diabetes management, (2) text messaging, and/or notification reminders on diet, physical exercise, and self-monitoring, and (3) in-app services to track self-monitoring, diet and steps. This is followed by weekly online surveys to improve awareness on self-management. An example of each of these are shown in Figures 1 to 4. This study will focus on only a retrospective analysis based on compliance ratio, and a forward-looking prediction based on engagement ratio, for evaluation purposes.

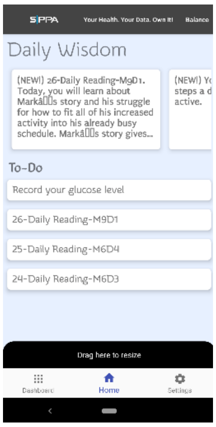

Figure 3: In-app service.

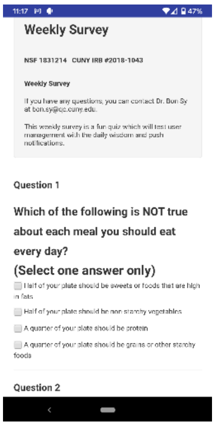

Figure 4: Weekly survey.

5.1 Data-driven Model Development

The data collected and used for this preliminary study are a subset of our pilot sample. When a subject enters the "intervention" phase of the study protocol, the SIPPA Health platform collects de-identified activity meta-data on user interactions with the SIPPA Health mobile app. This allows us to infer adherence and engagement in certain activities; e.g., using the app to conduct medication research or schedule medication reminders. The survey response data of 148 subjects were used to derive individuals' behavior readiness. Among the 148 subjects, 49 of them have either completed the study or were in the "intervention" phase during the study period. The data from these 148 subjects were used for the manifold clustering to identify subpopulation characteristics defined by behavior readiness. The data from the 49 subjects just mentioned were used to derive the population-based models (**section 4.3 stage 3**) to support the behavioral predictive analytics for personalization. The personalization results reported in this paper are based on 22 subjects who were in the "intervention" phase during the study period of this research. A subject in the "intervention" phase of the study receives a recommendation on a weekly basis about the activities on diet management, physical activities, and self-monitoring of glucose and other vital signs. Personalization for each subject is performed on a weekly basis to recommend one activity to focus on during a week.

Using the behavior readiness of 148 subjects as training data, four manifold clusters were identified. Each of the 49 subjects who completed/entered the intervention phase were assigned to a cluster based on the similarity of the behavior readiness measure between the individual and behavior patterns exhibiting statistically significant association that define the cluster. Further details on the similarity function could be found elsewhere (Sy, 2019).

Within each cluster subpopulation, a normalized compliance ratio and an engagement ratio of each subject, as well as the change on a weekly basis, are derived for each one of the activities: diet management, physical activities, and self-monitoring. Each ratio is normalized to account for the different starting times of the participants. For each subject, an auto-regression model is derived for each activity for each ratio. It is noted that developing an auto-regression model is not always feasible. For example, there may not be sufficient data because in an early stage of the participation an individual may have only activity data in one category (such as self-monitoring) but not the others (such as physical activities). Furthermore, the data may not yield a valid auto-regression model because it fails the statistical test in step 3 during the model selection process using *BIC/AIC*. Typically, this happens when a subject is in the intervention phase for less than four weeks.

In a scenario where an individual auto-regression model is not feasible, prediction for personalization for the individual will rely on the population-based model. For each cluster subpopulation, we derive a population-based model − one for each activity − defined by the distribution of the compliance/ engagement ratio and the amount of change using the data of all the subjects in the cluster subpopulation. In other words, there are nxm such models to capture engagement (compliance) ratios; where n is the number of clusters, and m is the number of activity categories. For example, $m=3$ if there are three categories of activities such as diet management, physical exercise, and self-monitoring. A population-based model developed for an activity category Aj (where $j = 1 .. m$) in a cluster Ci (where $i = 1 .. n$) is used to predict an engagement (compliance) ratio for an individual in Ci when an individual auto-regression model is not available for the activity category Aj.

5.2 Preliminary Study

The subjects included in this study were distributed across four different clusters (subpopulations). The results reported in this paper are based on an 11-week (2.5 months) study of personalization in summer of 2020. In other words, the activity data of each subject since participating in this pilot, leading up to the week of personalization, was used to develop the prediction models for the self-management activities. Then for each subject a recommendation (either exercise or diet management) was derived using the prediction algorithm described in the previous section.

5.2.1 Feasibility Assessment

To determine the feasibility on the real-world application of the proposed behavioral predictive analytic technique, the design of the preliminary study consists of two parts. The first part is a retrospective analysis using the data related to compliance. The second part is looking forward prediction on the engagement. The purpose of retrospective analysis is to establish a base reference for performance assessment based on historical results. The looking forward prediction is for evaluating the prediction performance as a time series on a rolling basis in real time.

Retrospective Analysis

The predictive analytics will be greatly simplified if personalization could be based on only the time-series (engagement/compliance) data. That is, for each subject, it is possible to derive an auto-regression model that is also statistically valid according to the information-theoretic model selection criteria described in section 4.2. In such a case, manifold-based clustering could be completely skipped because a population-based model to support personalization would not be necessary.

To gain insight into such scenario just described, an attempt was made to derive an auto-regression model for each subject who completed/entered the intervention phase. Out of the 49 subjects, the auto-regression model derivation was successful for 21 subjects (who completed or entered the intervention phase). Therefore, manifold clustering is required for this particular use case on applying the algorithm described in section 4.3.

The compliance ratio is computed on the weekly basis for each subject. A subject has *n* data points of compliance ratio; where *n* is the number of weeks of participation in the intervention phase. For deriving the auto-regression model for a subject, *(n-4)* data points were used to derive/train the auto-regression model, and the model is used to predict the compliance ratio of the last 4 data points for evaluation purposes.

Forward Looking Prediction

In contrast to the retrospective analysis, forward looking prediction involves only those subjects who were in the intervention phase during the study period. Out of the 49 subjects mentioned earlier, 22 of them were used to generate the engagement ratios and predictive analytics.

The engagement ratio of each active subject was computed on a weekly basis. Similar to the retrospective analysis, an estimated engagement ratio is derived for each week based on the predictive analytics technique described in section 4.3. The prediction was performed forward looking. For example, the prediction on engagement ratio for week *n (n=2 ... 11)* of the 11-week study period for a subject would be conducted at week *n-1*. Then the actual observed engagement ratio was recorded at week *n*. This forward looking prediction process was repeated ten times in the 11-week study period.

5.3 Results

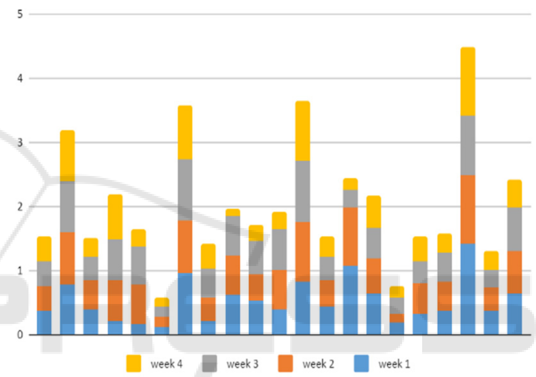

Figure 5: Predicted compliance ratio for an subject.

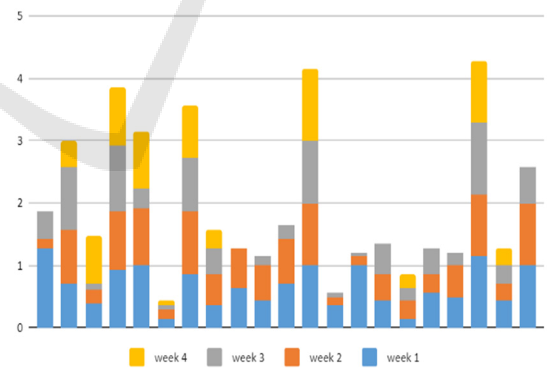

Figure 6: Observed compliance ratio for a subject.

5.3.1 Retrospective Analysis

Figures 5 and 6 show the predicted and observed compliance ratios of the 21 subjects for whom a statistically valid auto-regression model could be derived. The result shows the predicted and observed compliance ratios for each week on each of the 21 subjects; whereas a compliance ratio is derived based on a 7-day average. As shown in Figure 7, there is a consistent pattern across the 4-week prediction period. Below shows the R and the p-value of the 4 weeks; whereas R is the correlation coefficient measuring the strength and direction of a linear relationship between the predicted and observed compliance ratio, and p-value is a probability measure on the value of R that have occurred just by random chance (which is typically compared against the gold standard requiring it to be less than 0.05):

Table 2: R and p-values for the tests

	Week 1	Week 2	Week 3	Week 4
R	0.5178	0.6673	0.7698	0.7008
p-value	0.0162	0.00095	4.5E-05	0.0004

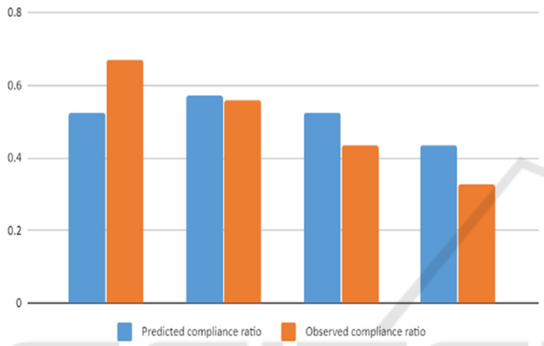

Figure 7: Average predicted vs observed CR.

5.3.2 Forward Looking Prediction

In the forward-looking prediction experiment, the prediction is on actionable health recommendations based on the maximal posterior estimate as described in section 4.3. In this study, the personalized actionable health recommendation would be in either diet management or exercise. 22 subjects were in the intervention phase during this period of research.

Figures 5 through 7 show evidence of its accuracy and consistency. But we are also interested in the effectiveness of the prediction technique for personalization. To evaluate its effectiveness for improving self-efficacy on health management, this study also attempts to show personalized actionable health (recommended by the behavioral predictive analytics) resulting in a more active engagement when it is compared to that of without personalization.

In order to understand the effect of personalization on engagement, the weekly average engagement ratio without personalization is compared against the engagement ratio with personalization. Figure 8 shows the aggregated weekly engagement average, disregarding subpopulations, for comparison purposes.

In calculating the engagement ratio without personalization, the average engagement ratio of each subject over time prior to personalization is first calculated, then the average over all the subjects. Note that the average engagement ratio of each subject over time prior to personalization spans over different time periods and lengths, as well as the actionable health recommendations because of the rolling nature of the subject participation in the pilot.

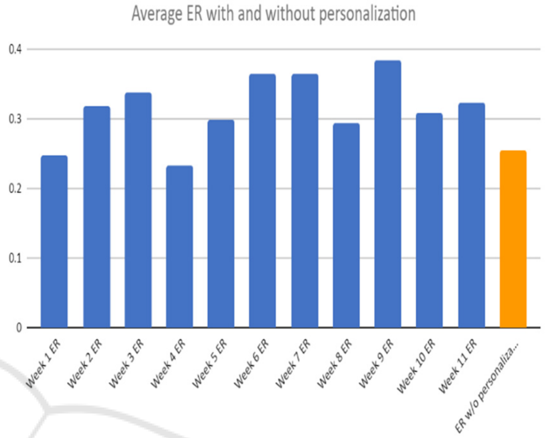

Figure 8: Aggregated ER w(/o) personalization.

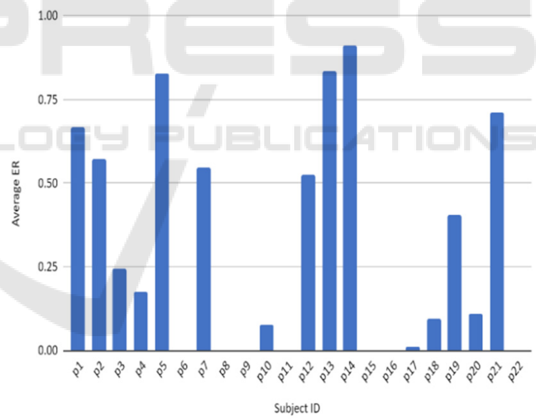

Figure 9: Individual ER average (over 11 weeks).

Figure 9 shows the engagement ratio of each individual averaged over the participation period. There are half a dozen subjects with low/zero engagement ratio in forward looking prediction. All of them received follow-up from this research team to understand these unusual outcomes. One withdrew from the study, and two were unreachable during the study period. Among the rest, one has limited technology proficiency, and one other older adult subject relies on her daughter to assist her on certain self-management activities at a time convenient to her daughter. Furthermore, one subject (participant 15 in

Figure 9) was active until he damaged his phone during the study period of this research.

Figure 10 shows the aggregated engagement average of 22 subjects (with personalization) for each week during the study period distributed across four cluster subpopulations.

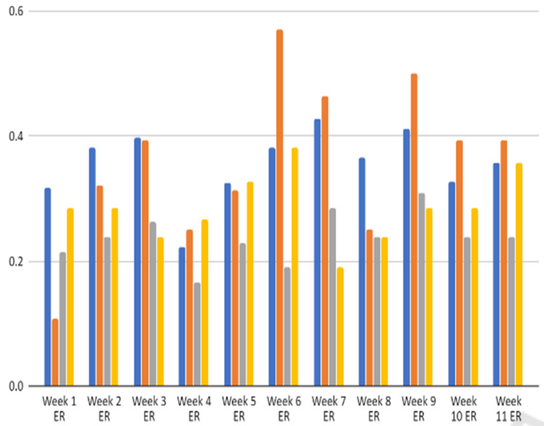

Figure 10: Observed ER by subpopulation clusters.

5.4 Discussion

5.4.1 Experimental Results

The results shown in Figures 5 through 7 in the retrospective analysis show evidence of the feasibility of behavioral predictive analytics in terms of computational efficacy as measured by accuracy and consistency.

Figure 8 shows the evidence of the applicability of the approach in terms of health efficacy. It shows that engagement level with personalization is better than that without personalization.

The results shown in Figures 9 and 10 in the forward-looking experiment demonstrate the practical implementation feasibility. The results shown in Figure 10 also reveal indirect evidence of the effectiveness of the manifold-based clustering technique for grouping subjects into subpopulations by means of behavior readiness. In particular, subpopulation clusters 1 and 2 are the more engaged patient subpopulations reflected in the behavior readiness characteristics of the clusters. Furthermore, personalization with strategies tailored for a cluster seems to show an effect over time for improving the engagement, in particular, the second cluster subpopulation that is not as high performing at the beginning.

Finally, the overall average engagement ratio with personalization had a mean value of 0.31 with a standard deviation of 0.33. The 95% confidence interval around this was [0.17, 0.45]. By contrast, without personalization, the overall mean engagement ratio is 0.26 with a standard deviation of 0.31. The 95% confidence interval for this value was [0.13, 0.38]. These are overall promising results; however, with such large standard deviations, one of the next steps in the research would be to gather larger samples to mitigate this issue.

5.4.2 Hypothesis Testing

Although the results shown in the previous figures are encouraging, it is necessary to conduct a hypothesis test analysis to understand the extent of improvement with clustering and personalization, as well as its statistical significance.

In reference to the results of the forward-looking prediction shown in Figures 8 to 10, an analysis was conducted to understand the effect of the population size on the statistical power. In particular, is the change in engagement ratio reported in this study generalizable?

This question was approached by conducting a t-test to compare the difference between the means of the engagement ratio with personalization and without personalization for the entire sample and within each cluster by investigating such change of each participant over the 11-week period of the study.

Table 3: Hypothesis testing results for each cluster.

	t-statistic	p-value
All data without clustering	0.51758	.303733
Cluster 1	0.32971	0.372949
Cluster 2	1.79319	0.061554
Cluster 3	-0.48247	0.319928
Cluster 4	-0.10798	0.459604

While the t-statistic shows an overall improvement on engagement ratio when personalization is applied --- irrespective to clustering, and a more significant improvement with clustering, none passes the p-value test for the result to be generalizable. This suggests that the study will need a larger population to achieve a power that allows the result to be generalizable.

5.4.3 Limiting Factors

There are many human factors that need to be explored in further analyses. These include time spent in the training period, level of proficiency with technology, and demographic features that can impact engagement such as gender and socioeconomic status.

In addition to the non-technical limitations above, two factors related to the population-based model are noteworthy. First, the population-based model approach is non-parametric and could potentially be sensitive to the additional data available over time that could change the behavior of the model as measured by information-theoretic entropy. Second, when a personalized recommendation is based on the population model, it should be noted that the prediction strategy is a “greedy” approach.

In reference to step 5 of the algorithm that determines the predicted value ΔER^{T+1}_p based on $Max\ Pr(\Delta ER^{T+1}_p |\ ER^T)$, a larger ΔER^{T+1}_p is unlikely to come from a large ER^T. For example, if $ER^T=0.9$, it is not possible for $\Delta ER^{T+1}_p > 0.1$; or $Pr(\Delta ER^{T+1}_p > 0.1 |\ ER^T=0.9)=0$. Therefore, the “greedy” approach has an inherent bias to work better in personalization for those who are moderately active compared to others.

6 CONCLUSION

A behavioral predictive analytics approach was presented for self-management personalization. The personalized recommendation is based on the engagement outcomes that reveal the behavior readiness of an individual in self-management. Auto-regression and population models were derived to support the proposed predictive analytics approach for generating personalized recommendations. A limitation of this research is the requirement for a “wait” period to accumulate sufficient data to derive a personalized auto-regression model. In this research we adopt a strategy that aims to prioritize personalization based on greatest improvement possible on engagement in a self-management area. This has an inherent bias that may negatively impact individuals with limited potential improvement on engagement. We do not yet know how this affects engagement and in what pace. Our future research will focus on understanding this aspect. An additional future research goal will be to collect larger samples in future, as our results were promising, but need larger samples to be statistically significant for future generalizability.

ACKNOWLEDGEMENTS

The authors are indebted to the reviewers for their valuable comments that help to improve this paper. This research is conducted under the support of U.S. NSF phase 2 grant 1831214. Mike Wassil oversees the pilot operation described in this research. Michael Van der Gaag leads the usability study of the mobile app used in this research. The pilot team consists of Arora Ashima, Connor Brown, Brandon Huang, Rebecca Horowitz, Sumaita Hussain, and Pan Lin. Dr. Catherine Benedict had advised on this research regarding patient self-efficacy. Dr. Adebola Orafidiya (MD) had helped this pilot team by sharing clinical best practice on recommending self-monitoring. This pilot team has also benefited from the discussions with Dr. Joseph Tibaldi (MD) and Caterina Trovato (CDE) on patient engagement.

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