SEM Approach for TPB: Application to Digital Health Software and Self-Health Management

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Abstract— **The goal of this research is to investigate the feasibility of Structure Equation Modeling approach for developing a quantitative behavior model grounded on the Theory of Planned Behavior. Data collected from an IRB sanctioned pilot consisting of approximately 500 participants were used to develop the model. The validity of the model is evaluated based on Chi-square, p-value, and RMSEA for statistical power and goodness of fit. The utility of the model is studied through correlation analysis related to user engagement for self-health management. Example association pattern discovered from the analysis was illustrated for its use in digital health software development.**

Keywords— Theory of Planned Behavior; Structure Equation Modeling; Digital Health; User Engagement; Self- Management.

I. INTRODUCTION

This research investigates the feasibility of developing a quantitative behavior model based on the Theory of Planned Behavior. The success of such a quantitative model will allow the application of machine learning and information-theoretic approach to discover statistically significant association patterns. Such patterns could inform the alignment between digital health services and motivation indicators for assessing the effectiveness of a BCT (Behavior Change Technique) for self-health management of chronic disease(s).

The total cost of health care services reported by CDC in 2012 is $2.7 trillion [1]. Of these expenditures, 86% were attributed to patients with chronic disease. Approximately 50 percent of the US population has one or more chronic disease. Chronic disease is the single largest burden to the health care system, accounting for 81% of hospital admissions, 91% of all prescriptions and 76% of physician visits [2]. In a recent CDC National Diabetes Statistics Report [3], 30.2 million people in the US are afflicted with chronic diabetes. Most of which suffer from either obesity, high blood pressure, high cholesterol, physical inactivity, smoking or a combination of these conditions. The direct and indirect cost of diabetes on the health care system amounted to $245 billion, with each patient costing the system $13,700 per year, which is 2.3 times the average of all patients [4].

It has been shown time and again that patient engagement leads to better care outcome and reduces cost burden on the healthcare system. However, patient engagement relies on the readiness, and willingness, to take ownership on self-health management. Yet there is a lack of quantitative models to assist on understanding the alignment between the delivery of digital health service and motivation indicators to engage an individual in self-management of chronic diseases.

The contribution of this research is a Structure Equation Modeling (SEM) approach for developing a quantitative behavior model, referred to as SIPPA-SEM-TPB. An objective of this research paper is to show through one use case how the SEM approach is applied to develop SIPPA-SEM-TPB, and how SIPPA-SEM-TPB model was used to better understand the motivation, intention, and attitude of an individual in regard to their readiness and willingness to engage in self-health management through digital health services delivered to them.

In section II the current state-of-art on patient assessment for readiness in self-health management will be discussed. The significance of this research will be discussed in the context of remote self-monitoring of chronic diseases. In section III the Theory of Planned Behavior and its clinical efficacy reported elsewhere will be summarized. In section IV we will present the statistical technique behind the SEM and the briefly discuss the related surveys for discovering the SIPPA-SEM-TPB. In section V we will discuss the result of the IRB sanctioned pilot, and the use of the pilot data to validate SIPPA-SEM-TPB. In section VI a use case will be illustrated to demonstrate the incorporation of SIPPA-SEM-TPB into the strategy design pattern of UML [5] for digital health software development. The conclusion section will discuss our future research.

II. STATE-OF-THE-ART

Telehealth has been in a rapid growth in the last few years and is projected to reach a market size of $30B [6]. Remote patient monitoring (RPM) falls under the umbrella of telehealth and aims to reduce the risk of ER visits and to slow down the progression of a chronic disease through self-monitoring while the data gathered by patients at home are made instantly available for the care providers at a remote location. Typically a RPM program requires a patient to be assessed prior to an enrollment. The assessment is to determine whether a patient is ready to be *activated* for self-monitoring. Various assessment tools are currently available.

In order to gauge how effective a patient could be engaged in self-health management including self-monitoring, an

Planned Behavior as a starting point for the development of a quantitative model just mentioned.

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assessment tool for RPM ideally should determine (1) the level of readiness in terms of motivation and skill, (2) the likelihood of behavior change overtime, and (3) underlying relationship linking motivation, attitude and intention to behavior change. Stanford [7] has published a set of evaluation tools for diabetic self-management. The evaluation tools consist of survey questions, scales, and the statistics on the score, such as average and standard deviation, from the population of their study. PAM13 is a commercial assessment tool that could be licensed from Insignia Health [8]. PAM13 is a 13-question survey for patient activation measure. PAM13 and Stanford assessment tools both place a focus on self-efficacy measure. The readiness of a patient for an activation in self-management is linked to self-efficacy. Linden et al [9] published an article to summarize a number of theory-based behavior models - Natural Helper Model, Diffusion of Innovations Model, Theories of Organizational Change, Community Coalition Action Theory, Social Marketing Model, Precede-Proceed Model, Motivational Interviewing, Stages of Change Model, Social Learning Interpersonal Theory, Consumer Information Processing Model, Implementation Individual Intentions Models, and Health Belief Model. While these models were discussed in terms of the theories behind, applications, and limitations for disease management, these models are not necessarily focused on individual level. For example, Theory of Organizational Change Model targets at disease management programs in the community level and focuses on the planning and implementation of population-based interventions that influence social norms and structures.

Recently, Theory of Planned Behavior Model [10], Transtheoretical Model of Behavior Change [11], Health Belief Model [12], and IMB (Information Motivation and Behavior Skill) Model [13] have been applied to specific intervention of chronic diseases, and have shown clinical efficacy. It was suggested that individuals perceiving risk of a condition are more likely to engage in behavior to reduce risk. Thus perceived health risk, resulting in change of attitude and behavior are proponents for higher intentions to be physically active and to maintain a healthy diet.

As evidenced by an already large body of knowledge and existing models, this research is not intended to re-invent the wheel. Rather, this research aims to develop quantitative model grounded on a behavior theory that has already been applied and shown efficacy in clinical studies. More specifically, such a quantitative model should help to reveal the linkage among behavior constructs, and should provide inference power to gain insights into not just the level of readiness in terms of motivation and skill for self-management, but the underlying relationship linking motivation, attitude, and intention to behavior change affected by the digital health services delivered in a mobile platform. Towards this end, this research will adopt the Theory of

III. THEORY OF PLANNED BEHAVIOR

The Theory of Planned Behavior (TPB) [10] provides a model to manifest the relationship among attitude, subjective norm, perceived behavioral control, intention and behavior. TPB is modeled through expectancy-value and assumes the best single predictor of an individual's behavior is an intention to perform that behavior. The intention in turn depends on the attitude of an individual (positive or negative evaluation of performing a behavior); the subjective norm (perception of whether relevant others think one should or should not perform the behavior); and perceived behavioral control (perception of the ease or difficulty of carrying out a behavior).

The TPB has been applied to study a variety of healthrelated behaviors, with attitude and perceived behavioral control having the strongest association with intentions and behavior [14]. Downs [15] and Hausenblas [16] have reported the efficacy of the TPB to explain physical activity, while Conner [17] and Sjoberg [18] have reported the effectiveness of TPB to explain diet activity. Blue [18], on the other hand, applies TPB to investigate the cognitive factors relevant to physical activity and healthy eating intentions or behaviors of diabetic patient population.

The goal of our model SIPPA-SEM-TPB is to incorporate SIPPA platform for delivering digital health services into a behavior model illustrated below:

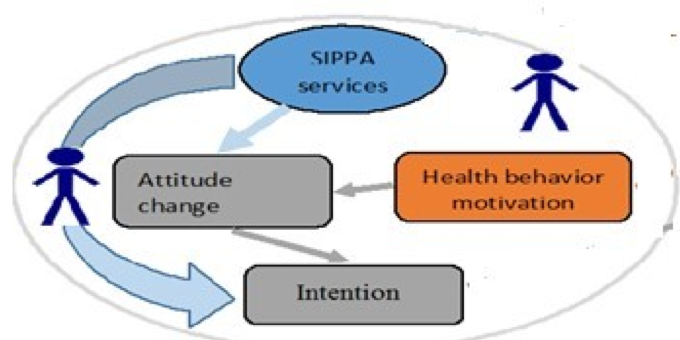


Fig. 1. Model incorporating SIPPA services with TPB

In the above diagram, SIPPA services are delivered via a

platform solution to a mobile device. This allows an individual to access multiple personalized services ranging from medication research, reminder, to encryption/decryption and import/exchange health data in an interoperable format under common standard of Meaningful Use. The SIPPA platform enables a patient centric approach for privacy preserved data collection to gain understanding on the impact of social, economic, and "non-clinical" behavioral lifestyle considerations on health. The details of the SIPPA technology platform is beyond the scope of this research. Readers interested in further details are referred to the publication elsewhere [19].

IV. STRUCTURAL EQUATION MODELING

The origin of Structure Equation Modeling (SEM) is evolved out of research across various disciplines [20-24]. This research follows the LISREL model [23] for SEM that takes into consideration of measurement errors in observed variables, but could be simplified if measurement error is negligible.

In general, SEM consists of two parts. The first part is a set of equations that give the causal relations between the substantive variables of interest, referred to as "latent variables," which are not observable. In our case, this includes *attitude, intention, motivation,* and *ownership* (regarding taking control). The latent variable model gives the causal relationships between these variables when the measurement error is absent or negligible. Mathematically, it is represented as below:

$$\eta_i = \alpha_n + B\, \eta_i + \Gamma\, \xi_i + \gamma_i$$

In the equation above, η_i is the ith vector of latent (endogenous) variables. α_n is the vector of intercepts. B is the matrix of coefficients that give the expected effect of the η_i on η_i where its main diagonal is zero. ξ_i is the vector of latent exogenous variables. Γ is the matrix of coefficients that give the expected effects of ξ_i on η_i. γ_i is the vector of equation characterizing the disturbances that consists of all other influences on η_i not included in the equation. Furthermore, the latent variable model also assumes that the mean of the disturbances is zero (i.e., $E(\gamma_i)=0$) and that the disturbances are uncorrelated with the latent exogenous variables (i.e., $Cov(\gamma_i,\ \xi_i)=0$). If the Cov is not zero, then those variables correlated with the disturbances are not exogenous and are included as an endogenous latent variable in the model. This is our case in regard to the latent variable *ownership*.

While the elements of the covariance matrices of ξ_i and γ_i could be manually determined to be freely estimated, constrained to zero or other values, we rely on the LISREL software to make the determination.

The second part of SEM connects the observed variables with the latent variables as below:

$$y_i = \alpha_y + \Lambda_y\, \eta_i + \varepsilon_i\, x_i =$$

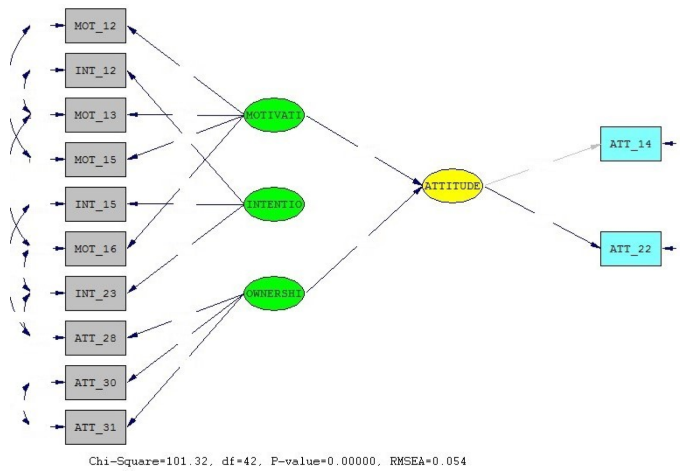
$$\alpha_x + \Lambda_x\, \xi_i + \delta_i$$

In the measurement model above, x_i and y_i are the vectors of indicators of ξ_i and η_i respectively. α_x and α_y are the vectors of intercepts. Λ_y is the loading factor matrix that gives the expected effects of η_i on y_i. ε_i is the vector of disturbances consisting of influences on y_i that are not part of η_i. Λ_x is the loading factor matrix that gives the expected effects of ξ_i on x_i. δ_i is the vector of disturbances consisting of all influences on x_i that are not part of ξ_i. Finally, the measurement model assumes a zero mean of disturbances and different disturbances are uncorrelated. Again, the elements of the covariance matrices of ε_i and δ_i could be manually determined to be freely estimated, constrained to zero or other values.

In SEM, one could incorporate causal assumptions as part of the model. This is our case. We assume that there is a causal relationship between *motivation, intention, ownership* and *attitude*. To simplify our assumptions and models, we assume the measurement errors of all variables negligible or zero. This is achieved through manual filtering of obvious pilot data that are error prone; e.g., contradictory responses. This allows us to set $y_i = \eta_i$ and $x_i = \xi_i$ and reduce the SEM formulation to below:

$$y_i = \alpha_n + B\, y_i + \Gamma_i\, x_i + \gamma_i$$

In the practice of SEM approach, one can choose to make strong or weak causal assumptions, as well as whether two disturbances are uncorrelated or not. In this research, we tried different assumptions and settled with the one that yields the "best" model in terms of statistical power and goodness of fit. The architecture of the final SIPPA-SEM-TPB model is shown below:



<u>Fig. 2. Architecture of casual SIPPA-SEM-TPM model</u>

In brief, each observable variable (*MOT_xx, INT_xx, ATT_xx*) in Fig. 2 corresponds to a survey question. Each possible response to a survey question is designed and is gone through a team discussion on its relevancy to the behavior constructs: *motivation, intention, attitude* and *ownership*. Further details on this model will be given in the next section.

V. PILOT STUDY AND SIPPA-SEM-TPB MODEL VALUDATION

The development of the Structure Equation Model discussed in this research paper is based on the data collected under an IRB sanctioned pilot (CUNY IRB #2016-0797). This pilot consists of five components below:

- Component 1: Initial screen survey consisting of 30 questions for polling data related to eligibility, chronic conditions, social determinants and lifestyle.
- Component 2: Orientation for enrolled participants, installation and configuration of SIPPA Health mobile app, as well as the collection of informed consent.
- Component 3: Pre-pilot 13-question survey with questions related to *motivation, intention, attitude* and *ownership*.
- Component 4: Remote self-guided exploratory session to carry out five specific tasks using SIPPA Health mobile app, as well as participating in an exit survey.
- Component 5: Post-pilot de-brief interview.

<u>@Component 1:</u> Approximately 500 subjects participated in the initial online screen survey. Their responses form the basis for the development of SIPPA-SEM-TPB model. These subjects were recruited from multiple sites. 38% of them are female. About 50% has a household income of less than $50K, 30% between $50K and $100K, and 20% has a household income of over $100K. About 44% of the population has less than 2 years of college study, 36% has two to four years of college study, and 20% has been in a graduate program. 15% reports to work/study over 50 hours a week, 35% between 36 hours and 50 hours, and 50% of them work/study less than 36 hours a week.

Among the 500, approximately 120 completed only partially the screen survey. Among the rest, 84 expressed interest and satisfied the inclusion/exclusion criteria to be enrolled. Since the pilot requires participants to engage with an Android app, the inclusion criteria include (1) age 18 or older, (2) basic internet computing skill and (3) the possession of an Android device.

@Component 2: Each of the 84 participants enrolled into the pilot is asked to sign the informed consent, and is assigned to one of the four handlers in this research team.

The handlers contacted participants by email, and arranged a schedule for an orientation. During the orientation, a participant returns the signed informed consent, and works with the handler to install and configure the SIPPA Health mobile app, as well as to download two test patient health records. The participant is also explained that SIPPA Health mobile app will track the meta-data of the usage such as the time and date, as well as the usage frequency of each service of the app. But no sensitive/private information will be recorded.

A handler also gave a demo and walked through the steps for using the SIPPA Health app on the following five tasks:

- Import, encrypt, decrypt, and view a test health record in interoperable format CCD [25].
- Consolidate the information in the second test health record by merging two records using SIPPA Health.
- Research medication information of interest, and set reminder for medication adherence.
- Participate in online survey delivered to the SIPPA Health app about nutrition education and therapy.
- Experiment video conference to simulate the interaction between a patient and a remote care provider through teleconsultation.

@Component 3: A pre-study survey of 13 questions extracted from the screen survey is provided to each subject. The survey response from each subject is used to establish a baseline about the level of engagement quantified in terms of the behavior constructs modeled as latent variables in Fig 2. Specifically, an inverse SIPPA-SEM-TPB model was derived to predict quantifiable behavior constructs; i.e., given a survey response and the inverse model, linear regression could be performed to derive the quantified behavior constructs.

The basis for deriving the inverse model is the SIPPASEM-TPB model developed using the response data of approximately 500 participants in component 1. The architecture of the final version of the model is shown in Fig. 2. The model is validated following the criteria and thresholds commonly agreed upon in the research community:

Criteria for good fit/significance **SIPPA-SEM-TPM**

At degree of freedom = 42,

1. Alpha=0.0025 ⇔ Chi-square = 72.32 **Chi-square=101.32**
   Alpha=0.005 ⇔ Chi-square = 69.336
2. p-value < 0.005 **p-value = 0**
3. RMSEA < 0.06 **RMSEA = 0.054**

@Component 4: Each subject is asked to conduct a selfguided exploratory session. In this study, the self-guided exploratory session is no less than 4 days but no more than 17 days unless there is a special circumstance. During the selfguided exploratory session, a subject would interact with up to three surveys delivered online directly to their mobile device through SIPPA Health. These surveys targets at the nutrition education and therapy, and engage subjects to set goals for increasing whole grain intake. After the self-guided exploratory session is completed, each subject is asked to complete a post-study survey that is identical to the pre-study survey. Among the 84 participants, only the data from 52 participants were actually used in this pilot study. The data from the rest were not usable due to various reasons ranging from missing survey responses to contradictory responses; e.g., one responded "I know how to track my caloric intake and I do it almost every day." and "I've never tracked my caloric intake." in the pre- and post- study survey respectively.

Of the 52 participants, the quantitative measures on the *motivation, intention* and *attitude* are again derived from the inverse model for each individual, and compared against the individual's baseline obtained from the pre-study response. The quantitative changes on *motivation (ΔMot), intention (ΔInt), attitude (ΔAtt),* and *ownership (ΔOwn)* are computed, resulting in 52 data points on the change for each behavior construct. The correlations among the behavior constructs are investigated using (1) all 52 data points, (2) only the data points from those who self-reported to have at least one chronic condition, and (3) only the data points from those who self-reported to have no chronic condition. The results are tabulated and shown below:

Corr(*ΔMot*, *ΔAtt*)	0.58			
Corr(*ΔMot*, *ΔInt*)		0.30		
Corr(*ΔInt*, *ΔAtt*)			0.19	
Corr(*ΔMot*, *ΔOwn*)				0.24

Table 1. Correlation using all data

Corr(*ΔMot*, *ΔAtt*)	0.30			
Corr(*ΔMot*, *ΔInt*)		0.43		
Corr(*ΔInt*, *ΔAtt*)			0.07	
Corr(*ΔMot*, *ΔOwn*)				-0.03

Table 2. Correlation using data of those w/ chronic conditions

Corr(ΔMot, ΔAtt)	0.67			
Corr(ΔMot, ΔInt)		0.29		
Corr(ΔInt, ΔAtt)			0.24	
Corr(ΔMot, ΔOwn)				0.31

Table 3. Correlation using data of those w/o chronic condition

@Component 5: At the end of the study, each participant is scheduled for a de-brief interview to gather information that could not be captured statistically, and that could be used to check the consistency of the quantitative data captured.

VI. USE CASE SIPPA-SEM-TPB MODEL VALIDATION

The utility of the validated SIPPA-SEM-TPB model is illustrated through a novel application to software development. More specifically, we will illustrate the incorporation of behavior constructs into the consideration of strategy design pattern of UML [26] for developing DigitalHealth-Software-as-a-Service (DHSaS).

According to an article in HealthIT news in 2015, there were 165,000 health related mobile apps available. About a quarter of the apps are related to chronic disease management. Yet only 0.022% of the apps – 36 out of 165,000 - account for 50% of all those downloaded [27]. While most apps arguably attempt to facilitate information communication, few may have incorporated a design that makes explicit the objective on affecting healthcare outcome. There are even fewer apps that achieve usability as measured by the retention rate. Currently an app that can achieve a retention rate of 25% is considered a big success; i.e., 25% of the users who download an app use it on a daily basis. The disparity between the number of apps available and the number of apps being used actively could be attributed to:

1. Lack of motivation for an individual to engage in healthy behaviors.

2. Disconnection between the perceived value of digital health and an individual; thus lack of intention to acquire the behavior health skill needed to engage in a health intervention.

To alleviate the problems, SIPPA-SEM-TPB could be applied to discover the motivation indicator of an individual to improve user engagement, as well as to incorporate the characteristics of behavior constructs that aligns with the motivation indicator into the software requirement/ specification in the development process of the digital health software services. We illustrate one such use case below.

As described in the previous section, the inverse model of SIPPA-SEM-TPB was applied to identify change in *motivation, intention* and *attitude*. Data analytics was applied to discover the statistical significant association patterns that could be used to inform software requirement/specifications formulated in terms of strategy design pattern in UML. In brief, the concept of association pattern discovery can be described via an example below:

Let's assume a survey similar to the one described in the previous section was conducted. The response to the survey questions by a respondent could be represented as (X1:val^{X1}_i X2: val^{X2}_j … Xn: val^{Xn}_k); where X1 … Xn are the variables corresponding to the survey questions. A collection of responses to the survey becomes a data set on (X1 X2 … Xn). A statistical association measure for (X1:val^{X1}_i … Xp: val^{Xp}_k) is considered α-significant if the following two conditions are satisfied:

1. The support for (X1:val^{X1}_i … Xp: val^{Xp}_k), defined as *Pr(*X1:val^{X1}_i … Xp: val^{Xp}_k*)*, is at least α; i.e., *Pr(*X1:val^{X1}_i … Xp: val^{Xp}_k*)* $\geq \alpha$.

2. The interdependency of *{*X1:val^{X1}_i … Xp: val^{Xp}_k*}* as measured by mutual information measure *MI*(X1:val^{X1}_i … Xp: val^{Xp}_k)=Log_2*Pr*(X1:val^{X1}_i…Xp:val^{Xp}_k)/*Pr* (X1:val^{X1}_i)…Pr(Xp: val^{Xp}_k) $\geq \beta(\chi^2)^{\gamma}$; where β and γ are some scaling factors, and due to Pearson, $\chi^2 = (oi - ei)^2/ei$.

The technical details for discovering association patterns are beyond the scope of this research. Readers interested in this are referred to the publication elsewhere [28].

Association pattern discovery was applied to data collected from the IRB sanctioned pilot study (CUNY IRB #2016-0797). Due to the page limit, we show here three exemplary patterns from a set of 12 (and 10) statistically significant association patterns discovered out of 160 possible second order association patterns for the chronic (non-chronic) population:

For the population with at least one chronic condition(s):

ΔInt	ΔOwn	pr(ΔInt, ΔInt)	assoc	Chisquare χ^2	χ^2/2N	assoc - χ^2/2N
2	3	0.1818	0.5525	0.2970	0.0133	0.539
3	1	0.1818	0.8745	0.7576	0.0345	0.840

Table 4. Association patterns of population w/ chronic disease

For the population without chronic condition:

ΔInt	ΔOwn	pr(ΔInt, ΔInt)	assoc	Chisquare χ^2	χ^2/2N	assoc - χ^2/2N
2	2	0.2195	0.027	0.3164	0.0038	0.2662

Table 5. Association patterns of population w/o chronic disease

Since change in *intention* (*ΔInt*) is associated with change in ownership to take control (*ΔOwn*), and by cross referencing and comparing the correlation derived from the population data between the chronic and non-chronic patient population, one of the interesting findings reviewed by our analysis is below:

> *Individuals with a chronic condition shows a stronger ownership on achieving adherence as evidence by a strong correlation between the usage of medication reminder and the change in motivation (0.2035 vs 0.0323).*

Once the finding is confirmed and informs that there is an alignment between the motivation indicator of the individuals with chronic conditions and the reminder (service), strategic design pattern of UML (Unified Modeling Language) in software engineering is applied to develop the reminder digital health service. We show one such design below:

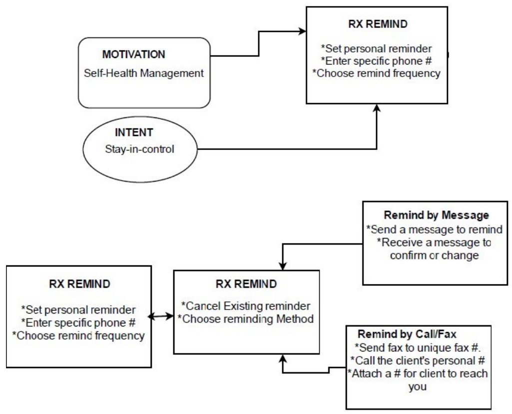


Fig. 3. Strategy design pattern of UML for reminder service

The screen shot of one such implementation of reminder service for the SIPPA Health service is show below:

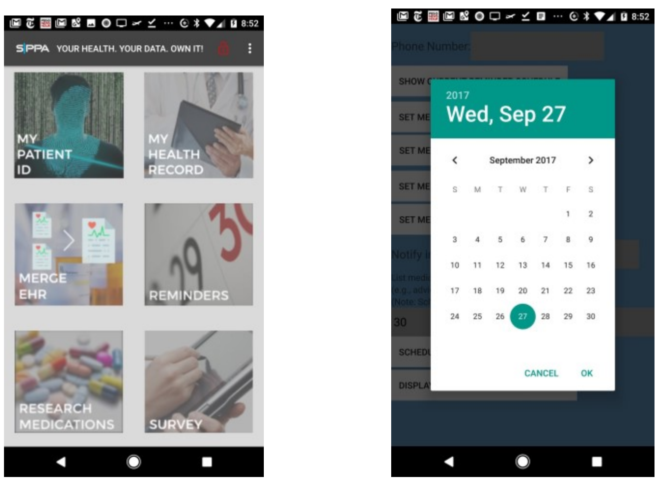


Fig. 4. Implementation of reminder service in SIPPA Health

VII. CONCLUSION

This paper presents a Structure Equation Modeling approach towards the development of a quantitative model for the Theory of Planned Behavior – referred to as SIPPA-SEM-TPB. Its feasibility is demonstrated through a pilot study in terms of statistical power and goodness of fit using commonly accepted criteria including alpha, p-value, and RMSEA. The utility of SIPPA-SEM-TPB was demonstrated for its application to incorporate behavior considerations into the strategy design patterns of UML. A use case based on the implementation of reminder service for medication adherence in the SIPPA Health mobile app was shown. Our future research will focus on understanding the effectiveness of our approach to improve care outcome based on self-health management of chronic disease(s) for disease specific patient population.

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The provisional application associated with this research is filed under U.S. 62/565,812.

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