A Longitudinal Observational Study Exploring the Sustained Usage of Technology-Enabled Intervention for Self-Monitoring of Blood Pressure in Public Primary Care Setting in Singapore

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Abstract

Background: Technology-enabled interventions for chronic disease management, such as telehealth systems for hypertension self-monitoring, have demonstrated effectiveness but face challenges with sustained usage and high attrition rates. Understanding the factors associated with continued engagement is crucial for enhancing intervention design and sustainability. This study investigates the sustained usage of the Primary Technology Enhanced Care for Hypertension Program (PTEC-HT) in Singapore's public primary care setting, focusing on patient adherence and the generation of Missed Reading (MR) alerts.

Objective: To explore the sustained usage of the PTEC-HT intervention by: (1) quantitatively describing characteristics of participants generating MR alerts, (2) identifying factors associated with MR alert generation, (3) profiling participant subgroups based on MR alert patterns and blood pressure (BP) control, and (4) examining temporal trajectories of MR alerts and associated conversion rates over 12 months.

Methods: A longitudinal observational study was conducted using backend data from the PTEC-HT system. The study included 491 participants, categorized into MR alert generator and non-generator groups, recruited before June 2022. Logistic regression identified factors associated with MR alert generation, while Latent Class Analysis (LCA) profiled participant subgroups. Generalized Estimating Equations (GEE) examined temporal trajectories of MR alerts and conversion rates. Statistical significance was set at 5%.

Results: MR alert generators were younger (mean age 58.6 years vs. 61.6 years; P=.011) and had a longer program duration (15.6 months vs. 15.0 months; P =.038). Age (OR 0.97, 95% CI 0.95-0.99; P =.007) and program duration (OR 1.11, 95% CI 1.01-1.22; P =.030) were significantly associated with MR alert generation. LCA identified three latent classes: (a) Compliant Triers (low MR alerts, poor BP control), (b) Compliant Achievers (low MR alerts, good BP control, 74.9% (368/491) of sample), and (c) Non-Compliant Achievers (high MR alerts, good BP control). Temporal analysis showed consistent trajectories for Missed Reading Reminder (MRR) message counts and conversion rates, with MR alert generators having higher MRR message counts but lower conversion rates compared to non-generators.

Conclusions: Sustained usage of the PTEC-HT program is influenced by age and program duration, with younger participants and longer durations linked to higher MR alert generation. The identification of distinct user profiles suggests that tailored intervention features could enhance engagement and BP control. The study underscores the importance of monitoring compliance patterns and optimizing message content to improve conversion rates. These insights contribute to the understanding of telehealth engagement dynamics and support targeted interventions for hypertension management.

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Conclusions: Sustained usage of the PTEC-HT program is influenced by age and program duration, with younger participants and longer durations linked to higher MR alert generation. The identification of distinct user profiles suggests that tailored intervention features could enhance engagement and BP control. The study underscores the importance of monitoring compliance patterns and optimizing message content to improve conversion rates. These insights contribute to the understanding of telehealth engagement dynamics and support targeted interventions for hypertension management.

Keywords: Telemonitoring; User-Engagement; Hypertension; User-Profile; User-Attrition; Remote Monitoring; User-Interaction; Telecare; E-health.

Introduction

Overview

While there is evidence to support that interventions involving self-management of chronic diseases by patient empowerment are effective [1-3], with an increasingly used modality being telehealth interventions, the flip side of telehealth interventions is the large attrition rate associated with time. It has been reported in literature that up to 80% of users of mobile apps often use such interventions minimally with high rates of drop out. [4, 5] Additionally, another observational study situated in real-world setting reported less than 5% of the participants having continuous usage of the mobile app. [6] A recent systematic review synthesizing quantitatively and qualitatively the evidence on attrition associated with mHealth interventions reported the dropout rate to be high (40% for 9 randomized controlled trial and 49% for 8 observational studies with an overall pooled rate of 43%). The reasons cited were social, demographic, and behavioural which were classified as modifiable. [7] This not only highlights the magnitude of the attrition problem but also provides the sound basis of studying the experience of sustained usage of technology-enabled interventions for self-management of chronic disease and the associated factors. This study would be addressing this gap with the use case of patients with hypertension within the Primary Technology Enhanced Care for Hypertension Program (PTEC-HT) in Singapore. [8]

PTEC-HT was developed to integrate telehealth solutions for hypertension management, emphasizing remote blood pressure monitoring, virtual care team support, and medication adjustments based on clinical guidelines. Its evidence-based design incorporated features such as automated feedback, patient reminders, data visualization, and educational resources, ensuring practical and effective implementation. The Ministry of Health Office for Healthcare Transformation (MOHT), an innovation-focused unit aimed at healthcare redesign in Singapore, [9] evaluated the program's effectiveness through a quasi-experimental pilot study. [10] Building on the pilot's success, MOHT has scaled PTEC-HT across the national public primary care system with the overall program duration being five years. This landmark initiative in telehealth for hypertension presents an opportunity to examine patient adherence to BP self-monitoring and sustained engagement with the system.

Within PTEC-HT, the key behaviour that patients are expected to undertake is regular weekly submission of their BP readings into the PTEC-HT app. Based on the structure of the PTEC-HT system including in-app prompts and reminders, if the patient fails to submit the indicated BP reading within 1 week, they receive in-app missed reading reminders (a total of 2 per missed reading) to remind them to complete this task. However, the patient may choose to ignore these prompts and after 4 consecutive weeks of no submitted readings, the care team in public primary care clinics get a Missed Reading (MR) alert on the PTEC-HT clinician dashboard with pre-decided follow-up actions, most common being calling the patient to find out the reason for MR alert. In real world setting, with increasing patient volume on PTEC-HT, not only is the studying of this dimension of how patients interact with the PTEC-HT system important from research and user-centred design perspective, but also from program sustainability perspective to manage the care team's workload. Hence, PTEC-HT provides us an excellent opportunity to learn about the sustained use of a telemonitoring and tele-support intervention by patients with hypertension within real world implementation context as well as explore the patient interaction with the PTEC-HT system. The insights gained will not only help with implementation and sustainability of the program but also add new knowledge to the existing literature.

Aims & Objectives

The overall aim of this study was to explore the sustained usage of a technology-enabled intervention (ie, PTEC-HT) in public primary care setting in Singapore. Following are the specific objectives:

1. To quantitatively describe the characteristics of sub-group of PTEC-HT participants who contribute to MR alerts on the clinician dashboard based on generation of MR alert during the index month.
2. To determine the factors associated with generation of MR alert during the index month in patients on PTEC-HT.
3. To explore and quantify different profiles of PTEC-HT participants generating MR alert

during the index month and describe the characteristics of these identified profiles.

4. To describe the temporal trajectories of generating missed reading reminders as well as the associated conversion rates by PTEC-HT patients over 12 months preceding the generation of MR alert during the index month.

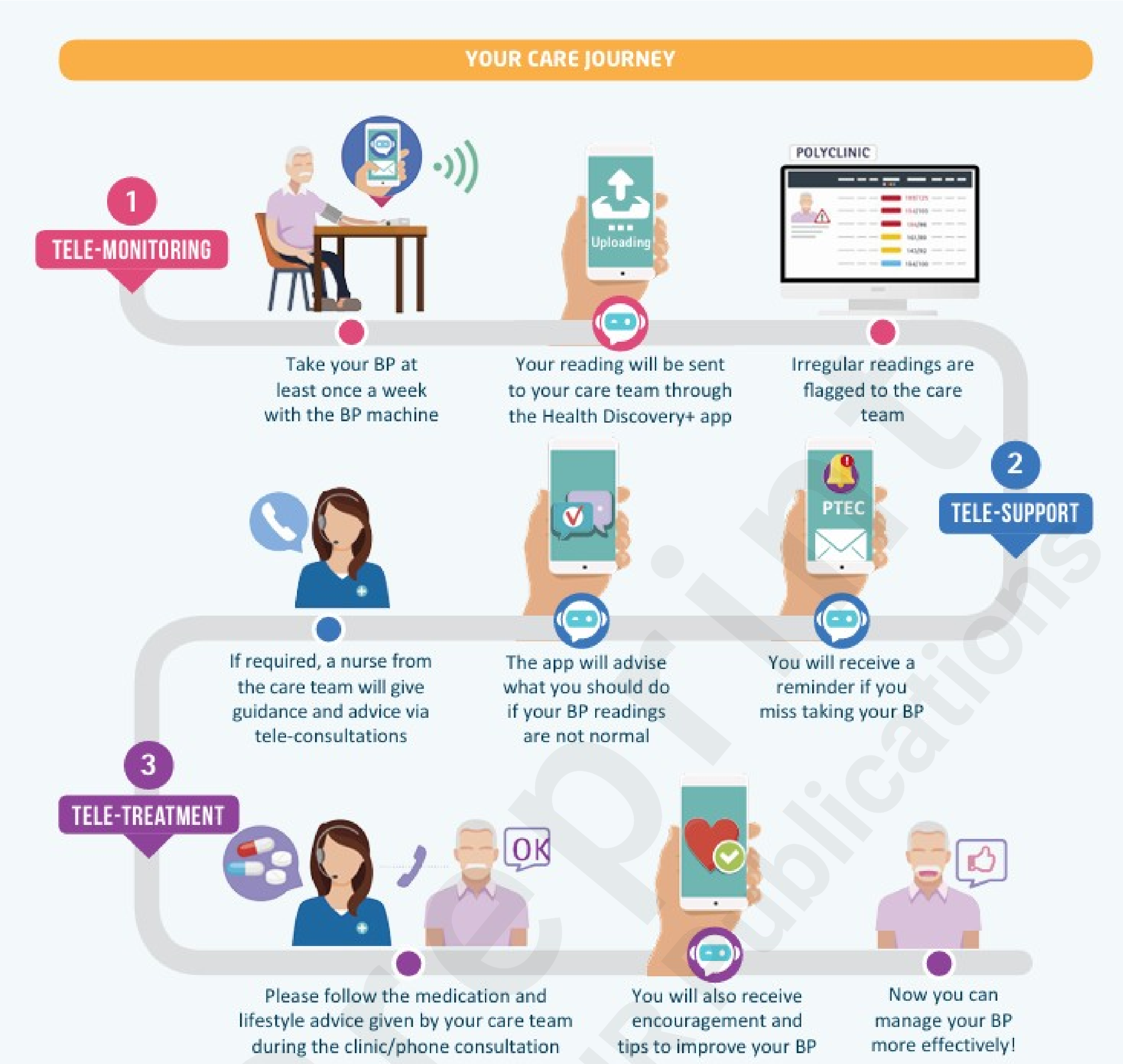
Methods

Background and Setting

The PTEC-HT Scaling Program is the first nationwide initiative under the Primary Technology Enhanced Care framework. It was launched in Aug 2020, being progressively scaled across all public primary care clinics within Singapore with the implementation timeline of 5 years. This innovative program seeks to empower patients with high blood pressure to take control of their condition from the comfort of their homes while receiving remote support from their healthcare team. It leverages simple, user-friendly technology and operates on the national IT platform, Smart Health Vital Signs Monitoring (VSM), developed by Synapxe, Singapore's health technology agency. [8] Patients with hypertension are eligible to participate if they are aged between 21 to 80 years, not pregnant at the point of recruitment, have history of high blood pressure, and have no history of atrial fibrillation, kidney failure or heart failure.

The program comprises three essential components designed to streamline care and improve patient outcomes. First, patients remotely monitor their blood pressure using a Bluetooth-enabled BP machine, recording readings at least once a week. These readings are automatically transmitted to their public primary care clinic via the PTEC-HT app. Second, the care team provides regular support by reviewing the transmitted data monthly. If a patient's condition is poorly controlled or requires medication adjustments, the team initiates tele-consultations to provide timely interventions. Third, in-app assistance offers interactive support through advice, reminders, and a chatbot, helping patients stay engaged and adhere to their care plan. [8] The workflow or care journey for patients participating in PTEC-HT is illustrated in **Figure 1**, highlighting the seamless integration of technology and healthcare support to promote better management of high blood pressure.

Figure 1. Patient Care Workflow or Journey within the PTEC-HT Scaling Program.



Data Collection

Adopting a longitudinal observational study design, the required data for this study was extracted from the PTEC-HT system backend. The operationalization of different time-points for this data extraction is provided in **Supplementary Table 1**. The study population comprised ‘MR alert generator Group’ and ‘non-MR alert generator Group’. While the ‘MR alert generator Group’ comprised PTEC-HT participants who contributed to generation of a MR alert in the month of Aug 2023 (ie, index period), the ‘non-MR alert generator Group’ comprised PTEC-HT participants who did not contribute to generation of a MR alert in the month of Aug 2023. For participants in both groups to be eligible, the PTEC-HT recruitment was anytime in June 2022 or before and no program termination between June 2022 to July 2023. The ‘non-MR alert generator Group’ comprised PTEC-HT participants who did not contribute to generation of a MR alert in the month of Aug 2023 and were recruited anytime in June 2022 or before. While data extracted over the first six months under the ‘observation period’ was used in computing the different profiles of PTEC-HT participants, data extracted over the twelve months under the ‘observation period’ was used in computing the temporal trajectories of generating missed reading reminders as well as the associated conversion rates for such reminders.

Variables

The main outcome of interest was generation of MR alert (ie, yes or no) during the index month. MR alert is generated on the clinician's PTEC-HT dashboard if a participant did not submit any BP readings in the preceding month. This information was extracted for the designated index month of August 2023. The covariates included in current analysis were as follows: age at recruitment, gender (ie, male or female), implementation site (ie, A, B and C), duration on PTEC-HT, and baseline BP control. Implementation sites represented the three clusters of public primary care clinics within Singapore across which the program was implemented. The duration on PTEC-HT was computed based on PTEC-HT recruitment date and index month over which MR alert generator status was confirmed. Baseline BP control was defined based on first BP reading submitted at the point of recruitment. A participant was categorized as having baseline BP control if they had both systolic BP <140 mm Hg and diastolic BP <90 mm Hg.

For generation of PTEC-HT participant profiles, MR alert generation (ie, yes or no), BP control status, and monthly submission frequency of BP readings were computed over the preceding six months from the contributing period. BP control status was coded as yes if the participant's monthly systolic BP was <140 mm Hg and diastolic BP was <90 mm Hg. For assessing the temporal trajectories of generating missed reading reminders as well as the associated conversion rates over 12 months preceding the generation of MR alert during the index month, following variables were extracted: Missed Reading Reminder A (MRRA), conversion to MRRA, Missed Reading Reminder B (MRRB), and conversion to MRRB. A participant would receive a MRRA if they did not submit any BP readings by the end of the week. Such message is triggered by the PTEC-HT system on every Saturday 7pm. Conversion to MRRA was categorized as yes if participant submitted BP reading after receiving MRRA message and before subsequent Monday, 9am. Conversion rate to MRRA was calculated as the proportion of total number of conversions (coded as yes) to the total number of MRRA messages received in a month. A participant would receive a MRRB if they did not submit any BP readings over the week. Such message is triggered by the PTEC-HT system on every Monday 9am. Conversion to MRRB was categorized as yes if the participant submitted BP reading after receiving MRRB message and before subsequent Wednesday. Conversion rate to MRRB was calculated as the proportion of total number of conversions (coded as yes) to the total number of MRRB messages received in a month.

Analysis

Descriptive characteristics were summarized using mean and standard deviation for continuous variables, number and proportion for categorical variables. The bivariate association between MR alert generator versus not and pre-determined covariates was assessed using t-test for continuous variables and chi-square test for categorical variables. Factors associated with generation of MR alert during the index month were assessed by running logistic regression [11] with the outcome variable being MR alert generation during index month (ie, yes or no). Logistic regression models were built in the following phased manner with Model I including the socio-demographic covariates of age, gender, and implementation site. Model II comprised of Model I covariates along with baseline BP control status. Model III comprised of Model II covariates along with duration on PTEC-HT. Odds ratio along with 95% confidence intervals for all three models are presented in the results section.

To describe the profiles of PTEC-HT participants, Latent Class Analysis (LCA) was conducted. LCA is a statistical method used to identify unobserved subgroups (latent classes) within a population based on observed data. [12] To identify latent classes, variables related to monthly MR alert generation, monthly BP control status, monthly compliance to BP submission frequency over six months were included. Models with 2 to 3 classes were tested along with different combinations of the above three categories of variables. 3-class solution comprising MR alert generation and monthly BP control status variables was selected as the best fit based on statistical indicators of Akaike

Information Criteria (AIC), Bayesian Information Criterion (BIC) [13] and interpretability of classes. (Refer to **Supplementary Table 2**)

Generalized Estimating Equation (GEE) approach was used to analyse the temporal trajectories of generating MRRA, conversion rate to MRRA, MRRB, and conversion rate to MRRB over 12 months preceding generation of MR alert. Liang and Zeger [14] proposed the Generalized Estimating Equation (GEE) method for analysing repeated measures data within the framework of Generalized Linear Models, offering estimates that reflect population averages. While Poisson distribution with a log link function was used for MRRA and MRRB data, binomial distribution with logit link was used for conversion to MRRA and conversion to MRRB data. We employed a working correlation matrix based on an exchangeable correlation structure and utilized the Huber-White sandwich estimator to derive robust variance estimates, ensuring reliability even in cases where the working correlation matrix was incorrectly specified. [14-16] A simple model was run initially to obtain the unadjusted trajectories for MRRA, MRRB, conversion to MRRA, conversion to MRRB with time (as month) as the independent variable (referred to Model A). Model A was subsequently adjusted for age, gender, implementation site, baseline BP control, and duration of PTEC-HT (referred to as Model B). Subsequently, MR alert generation (during index month) was added to Model B (referred to as Model C). With this Model C, we further added interaction terms between time variable and MR alert generation variable to determine if the temporal trajectories vary by MR alert generation status (referred to as Model D). Sample size calculation was not conducted since data for all eligible participants was extracted. Significance level was set at 5%. All analyses were performed using Stata/SE 17. [17]

This study was reviewed and approved by National University of Singapore's Institutional Review Board (NUS-IRB Reference Code: NUS-IRB-2024-1149).

Results

A total of 491 patient participants from the PTEC-HT program, who met the inclusion criteria, were included in the current analysis. The descriptive characteristics comparing MR alert generators with non-MR alert generators are given in **Table 1**.

Table 1. Descriptive characteristics of Missed Reading (MR) Alert generator (during index month) versus not (N=491)

Characteristic		**MR Alert in Index Month (Yes) (n=93)**	**MR Alert in Index Month (No) (n=398)**	**Total**	**P value**
Age in years, mean (SD)		58.6 (10.47)	61.6 (9.97)	61.0 (10.1)	**.011**
Age (years), n (%)					
	65 years or less	64 (68.8)	241 (60.6)	305 (62.1)	.14
	More than 65 years	29 (31.2)	157 (39.4)	186 (37.9)	
Gender, n (%)					
	Female	44 (47.3)	160 (40.2)	204 (41.5)	.21
	Male	49 (52.7)	238 (59.8)	287 (58.5)	
Implementation site, n (%)					
	A	14 (15.1)	93 (23.4)	107 (21.8)	.21
	B	63 (67.7)	240 (60.3)	303 (61.7)	
	C	16 (17.2)	65 (16.3)	81 (16.5)	
Duration on PTEC-HT Program (months)[a], Mean (SD)		15.6 (2.3)	15.0 (2.3)	15.1 (2.4)	**.04**

Baseline BP control[b], n (%)					
	No	54 (58.1)	235 (59.2)	289 (59.0)	.84
	Yes	39 (41.9)	162 (40.8)	201 (41.0)	

[a]Duration on PTEC-HT Program is computed based on time between recruitment date for a patient participant and start of the index month during which MR alert generator status was confirmed.
[b]Baseline BP control is defined based on first blood pressure reading submitted at the point of recruitment. A patient participant is categorized as having controlled baseline BP if they have both systolic BP <140 mm Hg and diastolic BP <90 mm Hg.

MR alert generators (mean 58.6, SD 10.5 years) were significantly younger than non-MR alert generators (mean 61.6, SD 9.97 years, *P*=.011). Additionally, there was a statistically significant difference (*P*=.04) between both groups for duration on PTEC-HT program with MR alert generators having a lower duration (mean 15.6, SD 2.3 months) as compared to non-MR alert generators (mean 15.0, SD 2.3 months). There was no statistically significant difference between both groups for gender, implementation site, and baseline BP control. Referring to adjusted analysis exploring the factors associated with generation of MR alert during the index month in **Table 2**, age of the participant as well as duration on PTEC-HT program were significantly associated with generation of MR alert during the index month.

Table 2. Factors associated with generation of Missed Reading (MR) alert (during index month) (N=491)

Characteristic		**Model I[a]**		**Model II[b]**		**Model III[c]**	
		OR[d] (95% CI)	**P value**	**OR[d] (95% CI)**	**P value**	**OR[d] (95% CI)**	**P value**
Age in years		0.97 (0.95-0.99)	**.008**	0.97 (0.95-0.99)	**.009**	0.97 (0.95-0.99)	**.007**
Gender with reference to female	Male	0.76 (0.48-1.21)	.25	0.76 (0.48-1.21)	.25	0.74 (0.46-1.17)	.20
Implementation site with reference to A	B	1.84 (0.98-3.47)	.15	1.83 (0.97-3.46)	.16	1.76 (0.93-3.35)	.16
	C	1.40 (0.63-3.11)		1.39 (0.62-3.10)		1.20 (0.53-2.72)	
Baseline BP control with reference to No	Yes			0.98 (0.61-1.57)	.94	1.03 (0.64-1.66)	.89
Duration on PTEC-HT Program in months						1.11 (1.01-1.22)	**.03**

[a]Model I: includes age, gender, implementation cluster.
[b]Model II: Model I and baseline BP control status.
[c]Model III: Model II and duration on PTEC-HT program
[d]OR is odds ratio

Specifically, older participants had lower odds of generating a MR alert as compared to younger participants (OR 0.97, 95% CI 0.95-0.99; *P* =.007).For every additional month on PTEC-HT program, the odds of generating a MR alert increased by 11% (OR 1.11, 95% CI 1.01-1.22; *P* =.030). While latent class membership and estimated probabilities of each observed variable are presented in **Table 3**, latent class size as well as key characteristics of each latent class are presented in **Table 4**. Following three latent classes were identified based prevalence of MR alert generation as well as BP control status over 12 months: latent class 1 or 'Compliant Triers', latent class 2 or 'Compliant Achievers', and latent class 3 or 'Non-Compliant Achievers'. 'Compliant Triers' were characterised by consistent trend of low probability of generating MR alert as well as low probability of having controlled BP. 'Compliant Achievers' were characterized by consistent trend of low probability of generating MR alert but high probability of having controlled BP. 'Non-Compliant Achievers' were characterized by consistent trend of high probability of generating MR alert as well as high probability of having controlled BP.

Table 3. Latent class membership and estimated probabilities of each observed variable (N=491)

Variable[a]		**Latent Class 1: Compliant Triers, Marginal Mean**[c] **(95% CI)**	**Latent Class 2: Compliant Achievers, Marginal Mean**[c] **(95% CI)**	**Latent Class 3: Non-Compliant Achievers, Marginal Mean**[c] **(95% CI)**
Missed Reading (MR) Alert	**M7**	0.20 (0.11-0.34)	0.04 (0.02-0.07)	0.72 (0.58-0.83)
	M8	0.06 (0.02-0.19)	0.06 (0.04-0.09)	0.65 (0.51-0.77)
	M9	0.11 (0.05-0.24)	0.04 (0.02-0.07)	0.78 (0.63-0.88)
	M10	0.09 (0.03-0.22)	0.04 (0.02-0.07)	0.76 (0.61-0.86)
	M11	0.14 (0.07-0.29)	0.05 (0.03-0.08)	0.70 (0.56-0.81)
	M12	0.15 (0.06-0.30)	0.06 (0.04-0.10)	0.70 (0.56-0.81)
Blood Pressure (BP) Control[b]	**M7**	0.44 (0.30-0.59)	0.97 (0.94-0.98)	0.74 (0.39-0.93)
	M8	0.38 (0.23-0.55)	0.98 (0.95-0.99)	0.82 (0.56-0.94)
	M9	0.55 (0.41-0.69)	0.99 (0.97-1.00)	0.71 (0.41-0.90)
	M10	0.49 (0.34-0.64)	0.98 (0.96-0.99)	0.81 (0.53-0.94)
	M11	0.48 (0.33-0.62)	1.00 (0.00-1.00)	0.76 (0.49-0.91)
	M12	0.40 (0.26-0.56)	0.98 (0.95-0.99)	0.87 (0.59-0.97)

[a]M7 to M12 denote Month 7 to Month 12.
[b]BP Control is defined categorised as yes if monthly average systolic BP is less than 140 mm Hg and monthly average diastolic BP is less than 90 mm Hg.
[c]Marginal mean presented here can have a value between 0 to 1 with values close to 1 indicating higher probability of the observed variable with the latent class.

Table 4. Latent class size and key characteristics (N=491)

Class Number & Name	**Size in sample, N (%)**	**Marginal probability (95% CI)**	**Key characteristics**
Latent Class 1: Compliant Triers	56 (11.4%)	0.12 (0.09, 0.17)	Consistent trend of low probability of generating MR alert and low probability of having controlled BP
Latent Class 2: Compliant Achievers	368 (74.9%)	0.74 (0.70, 0.79)	Consistent trend of low probability of generating MR alert and high probability of having controlled BP
Latent Class 3: Non-Compliant Achievers	67 (13.6%)	0.13 (0.10, 0.17)	Consistent trend of high probability of generating MR alert and high probability of having controlled BP

The most prevalent latent class identified in current sample of participants was latent class 2 or 'Compliant Achievers' with 74.9% (368/491) of total sample compared to the other two latent classes (ie, latent class 1 or ‘Compliant Triers’ and latent class 3 or ‘Non-Compliant Achievers’). Descriptive characteristics of identified latent classes are presented in **Table 5**.

Characteristics		Compliant Triers (n = 56)	Compliant Achievers (n = 368)	Non-Compliant Achievers (n = 67)	Total (N =491)	P value
Age in years, Mean (SD)		58.1 (9.8)	61.8 (10.0)	59.5 (10.4)	61.0 (10.1)	**.017**
Age in years, n (%)						
	65 years or less	41 (73.2)	218 (59.2)	46 (68.7)	305 (62.1)	.066
	More than 65 years	15 (26.8)	150 (40.8)	21 (31.3)	186 (37.9)	
Gender, n (%)						
	Female	21 (37.5)	153 (41.6)	30 (44.8)	204 (41.6)	.72
	Male	35 (62.5)	215 (58.4)	37 (55.2)	287 (58.5)	
Implementation site, n (%)						
	A	16 (28.6)	75 (20.4)	16 (23.9)	107 (21.8)	.21
	B	27 (48.2)	237 (64.4)	39 (58.2)	303 (61.7)	
	C	13 (23.2)	56 (15.2)	12 (17.9)	81 (16.5)	
Baseline BP control[a], n (%)						
	No	43 (76.8)	209 (56.9)	37 (55.2)	289 (59.0)	**.02**
	Yes	13 (23.2)	158 (43.1)	30 (44.8)	201 (41.0)	
Duration on PTEC-HT Program in days[b], Mean (SD)		471.6 (69.3)	471.6 (70.6)	493.6 (73.9)	474.6 (71.1)	.06
MR Alert in index month, n (%)						
	No	48 (85.7)	330 (89.7)	20 (29.9)	398 (81.1)	**<.001**
	Yes	8 (14.3)	38 (10.3)	47 (70.1)	93 (18.9)	

[a]Baseline BP control is defined based on first blood pressure reading submitted at the point of recruitment. A patient participant is categorized as having controlled baseline BP if they have both systolic BP <140 mm Hg and diastolic BP <90 mm Hg.

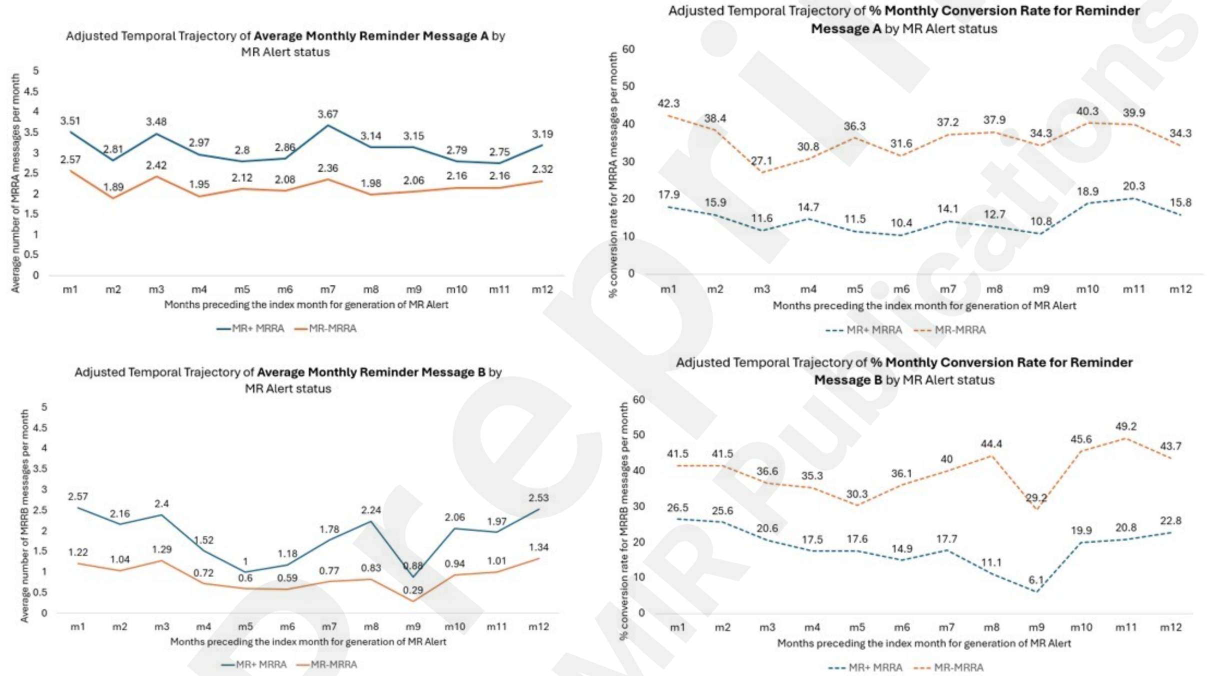
[b]Duration on PTEC-HT Program is computed based on time between recruitment date for a patient participant and start of the index month during which MR alert generator status was confirmed.

Table 5. Descriptive characteristics of identified latent classes (N=491)

The three latent classes had significant differences for age, baseline BP control as well as MR alert generation in the index month. The average age of ‘Compliant Achievers’ (mean 61.8, SD 10.0 years) was significantly higher than ‘Compliant Triers’ (mean 58.1, SD 9.8 years) and ‘Non-Compliant Achievers’ (mean 59.5, SD 10.4 years) (*P*=.017). Both ‘Compliant Achievers’ (43.1%, 158/368) and ‘Non-Compliant Achievers’ (44.8%, 30/67) had similar proportion of participants with controlled baseline BP at recruitment, and this was higher as compared to ‘Compliant Triers’ (23.2%, 13/56) (*P*=.015). ‘Non-Compliant Achievers’ had the highest proportion of MR alert generators during the index month (70.1%, 47/67) as compared to ‘Compliant Achievers’ (10.3%, 38/368) and ‘Compliant Triers’ (14.3%, 8/56) (*P*<0.001).

The findings for describing temporal trajectories of MRRA messages, conversion rate to MRRA messages, MRRB messages, conversion rate to MRRB messages are presented in **Supplementary Tables 3, 4, 5 and 6**, respectively under the Multimedia Appendix. Based on adjusted estimates from model 3, participants had a statistically significant consistent trajectory of generating MRRA messages ranging from 2.15 per month to 2.82 per month over 12 months preceding the index month of generation of MR alert (*P*<0.001) (Refer to **Supplementary Table 3 in Multimedia Appendix**). Additionally, participants had a statistically significant consistent trajectory for conversion to MRRA messages with conversion rate ranging from 23% to 36% per month over 12 months preceding the index month of generation of MR alert (*P*<0.001) (Refer to **Supplementary Table 4 in Multimedia Appendix**).Based on adjusted estimates from model 3, participants had a statistically significant consistent trajectory of generating MRRB messages ranging from 0.51 to 1.91 per month over 12 months preceding the index month of generation of MR alert (*P*<0.001) (Refer to **Supplementary Table 5 in Multimedia Appendix**). Additionally, participants had a statistically significant consistent trajectory for conversion to MRRB messages with conversion rate ranging from 20% to 40% per month over 12 months preceding the index month of generation of MR alert (*P*<0.001) (Refer to **Supplementary Table 6 in Multimedia Appendix**). The interaction term between time and MR alert generation in index month was statistically significant for all 4 temporal trajectories analyses. The adjusted temporal trajectories stratified by MR alert generation status (in index month) are presented for MRRA message monthly counts, MRRA message monthly conversion rate, MRRB message monthly counts, and MRRB monthly conversion rate in **Figure 2.**

Figure 2. Adjusted temporal trajectories of MRRA and MRRB message counts and associated conversion rates stratified by MR alert generation status



In summary, MR alert generators have consistently higher MRRA message and MRRB message monthly counts and consistently lower monthly conversion rates to both types of messages as compared to non-MR alert generators over 12 months preceding the index month of generation of MR alert.

Discussion

With the overall aim of exploring sustained usage of PTEC-HT in public primary care setting in Singapore, our analysis of 491 participants from PTEC-HT revealed significant differences between MR alert generators and non-generators. MR alert generators were younger (mean age 58.6 years vs. 61.6 years) and had a longer program duration (mean 15.6 months vs. 15.0 months). Age and duration in the program were significantly associated with generation of MR alert, with younger participants more likely to generate alerts and a monthly increase in duration associated with an 11% higher MR alert probability. Three latent classes were identified: (i) ‘Compliant Triers’ (with low MR alerts and poor BP control), (ii) ‘Compliant Achievers’ (with low MR alerts and good BP control), and (iii) ‘Non-Compliant Achievers’ (with high MR alerts and good BP control). ‘Compliant

Achievers' were the most prevalent group at 74.9% (368/491). Temporal trajectory analysis showed consistently higher MRRA and MRRB message counts among MR alert generators, but lower conversion rates compared to non-generators. These insights suggest distinct participant profiles with differing BP control patterns and alert generation tendencies, highlighting potential areas for targeted interventions to improve MR alert management and BP outcomes. We are the first to the best of our knowledge to report comprehensive findings on sustained usage of a nationwide implemented technology-enabled intervention for self-monitoring of blood pressure in patients with hypertension.

The results of our study align with and contribute to the growing body of evidence on the relationship between demographic characteristics, program duration, and telehealth intervention customization in the context of MR alert generation. Our findings indicated that younger participants were more likely to generate MR alerts, while older participants demonstrated more consistent adherence and lower alert generation. This aligns with previous studies, such as Wade et al. (2012) [18], which reported that older adults found telehealth technology increasingly easier to use over time, enhancing their sustained compliance. Along the same lines, another study reported that though older adults were less likely to choose to participate in a web-based self-management intervention, once enrolled, their intervention participation rates were similar to those of younger adults, and they tended to stay in the study longer than younger counterparts. [19] Additionally, in one of the recent studies, younger age was reported as the single strongest predictor of lower compliance in a virtual cardiac rehabilitation program. [20]

We observed that the duration of participation in the PTEC-HT was positively associated with increased MR alert generation. This is consistent with the literature indicating that telehealth compliance often diminishes over time. For instance, a literature synthesis exploring patient compliance with home-based self-care telehealth monitoring programs reported compliance to be highest in the initial phase. This initial compliance was reported to decrease over time. Some of the factors reported to help with improving patient compliance were patient's health literacy, telehealth implementation approach, training and user competency, and amount of human support incorporated in the intervention. [21] Another study similarly found that intermittent telehealth device use predicted earlier dropout from the program. [22] Thus determining the optimal duration for the program requires careful consideration of factors such as patient characteristics, financial resources, and available subsidies to maintain engagement and control MR alert generation effectively.

Our results revealed distinct latent classes with differing MR alert generation patterns, suggesting that customizing program features based on these user profiles may optimize compliance and outcomes. Seto and colleagues demonstrated the effectiveness of telemonitoring systems tailored to individual patients, highlighting the role of real-time feedback and ease of use in promoting adherence. [23] Similarly, another study emphasized the need for flexibility and regular human interaction in a tele-exercise program to maintain engagement over time. [24] These findings underscore the potential benefits of tailoring PTEC-HT features based on user-specific profiles, needs, and clinical outcomes.

The observed differences in MRRA and MRRB message prevalence and conversion rates between MR alert generators and non-generators underscore the importance of continuous compliance monitoring. It is reported in literature that early compliance patterns can predict long-term adherence, suggesting that regular monitoring of message interactions could help identify participants at risk of becoming disengaged. [25] This finding was further substantiated by a recent systematic review by associating early telehealth compliance with reduced dropout rates in patients with chronic obstructive pulmonary disease. [26] Proactive identification of declining engagement may allow timely interventions to prevent long-term non-compliance. Additionally, our analysis revealed statistically significant differences in MRRA and MRRB message trajectories between MR alert generators and non-generators, with generators consistently exhibiting higher message counts but lower conversion rates. This pattern indicates potential gaps in participant engagement despite increased messaging. The literature supports the importance of understanding message responsiveness over time. For example, Strandbygaard and colleagues observed that SMS text messaging reminders were more effective in the short term but lost impact over longer durations. [27] This aligns with our findings, suggesting that the diminishing effect of reminder text messages over time requires strategies such as dynamic text message content, varied communication channels, and periodic re-engagement activities to sustain long-term responsiveness.

Overall, our findings resonate with existing literature while providing new insights into the interplay of age, program duration, user profiles, and compliance behaviour in MR alert generation. Tailoring telehealth interventions based on these insights may optimize adherence and improve long-term outcomes in hypertension management programs like PTEC-HT. The findings from the analysis of MR alert generation in PTEC-HT highlight several actionable recommendations. Younger participants, who are more likely to generate MR alerts, would benefit from proactive engagement through educational sessions and digital tools. As program duration increases, additional support such as regular follow-ups and reminders can mitigate the rising trend of MR alerts. Tailored interventions based on latent class membership are essential: ‘Compliant Triers’ need BP control support (eg, up-titration of anti-hypertensive medication), ‘Compliant Achievers’ require sustained engagement, and ‘Non-Compliant Achievers’ would benefit from adherence-focused strategies. Moreover, improving MR message conversion rates through simplified content and educational efforts is crucial, given consistently high message generation but low conversion. Finally, regular monitoring of message trajectories can support early intervention, ultimately enhancing BP control and program effectiveness.

Following are the strengths of our study. This study utilized data from the PTEC-HT scaling program, a nationwide telehealth initiative implemented across all public primary care clinics in Singapore. The use of real-world, population-level data enhances the external validity of the findings, making the results more applicable to similar large-scale telehealth interventions. The longitudinal design enabled the tracking of MR alert generation, blood pressure control, and message interactions over a 12-month period. This approach allowed for the identification of temporal trends and patterns, such as the consistent decline in message conversion rates and the relationship between program duration and MR alert generation. By analysing MR alert generation patterns in conjunction with BP control status, participant compliance, and telehealth message interactions, the study generated meaningful insights into user behaviour. This granular level of analysis supports the potential for personalized telehealth interventions based on user profiles.

Our study has several limitations that warrant consideration. While we included a range of demographic, clinical, and engagement-related variables, we did not capture psychosocial factors such as patient motivation, technology literacy, or perceptions of telehealth interventions, which are factors known to influence adherence and engagement with digital health tools. This limitation is inherent in studies relying on IT system usage data and clinical outcomes without the inclusion of self-reported participant data. Additionally, we did not perform a formal sample size calculation, as the study utilized data from all eligible participants. Furthermore, the analysis did not adjust for external factors such as policy changes, participant life events, or evolving healthcare practices, which may have influenced telehealth engagement. We acknowledge the potential impact of these unmeasured confounders on the observed relationships between MR alert generation, BP control, and text message interaction patterns, though the feasibility of collecting such contextual data was limited within this study framework. Lastly, as the study was conducted in Singapore’s public primary care setting, the findings may not be fully generalizable to healthcare systems with different telehealth infrastructures, patient demographics, or care delivery models.

Conclusion

This study successfully met its objectives by quantitatively characterizing the subgroup of PTEC-HT participants who generated MR alerts, identifying key factors associated with MR alert generation, and exploring distinct participant profiles. Younger age and longer program duration were found to be significantly associated with MR alert generation, while latent class analysis revealed three distinct participant profiles with varying patterns of BP control and MR alert generation. Temporal trajectory analysis indicated consistently higher MRRA and MRRB message counts, coupled with lower conversion rates, among MR alert generators over the 12 months preceding the index month. Practical implications include tailoring intervention features based on user profiles, regularly monitoring compliance patterns to predict potential disengagement, and optimizing message content to improve conversion rates. Future research should explore psychosocial and behavioural factors influencing engagement, alongside strategies to maintain responsiveness as program duration increases. These insights contribute to the broader understanding of telehealth engagement dynamics and offer actionable recommendations for enhancing PTEC-HT's effectiveness in supporting hypertension management.

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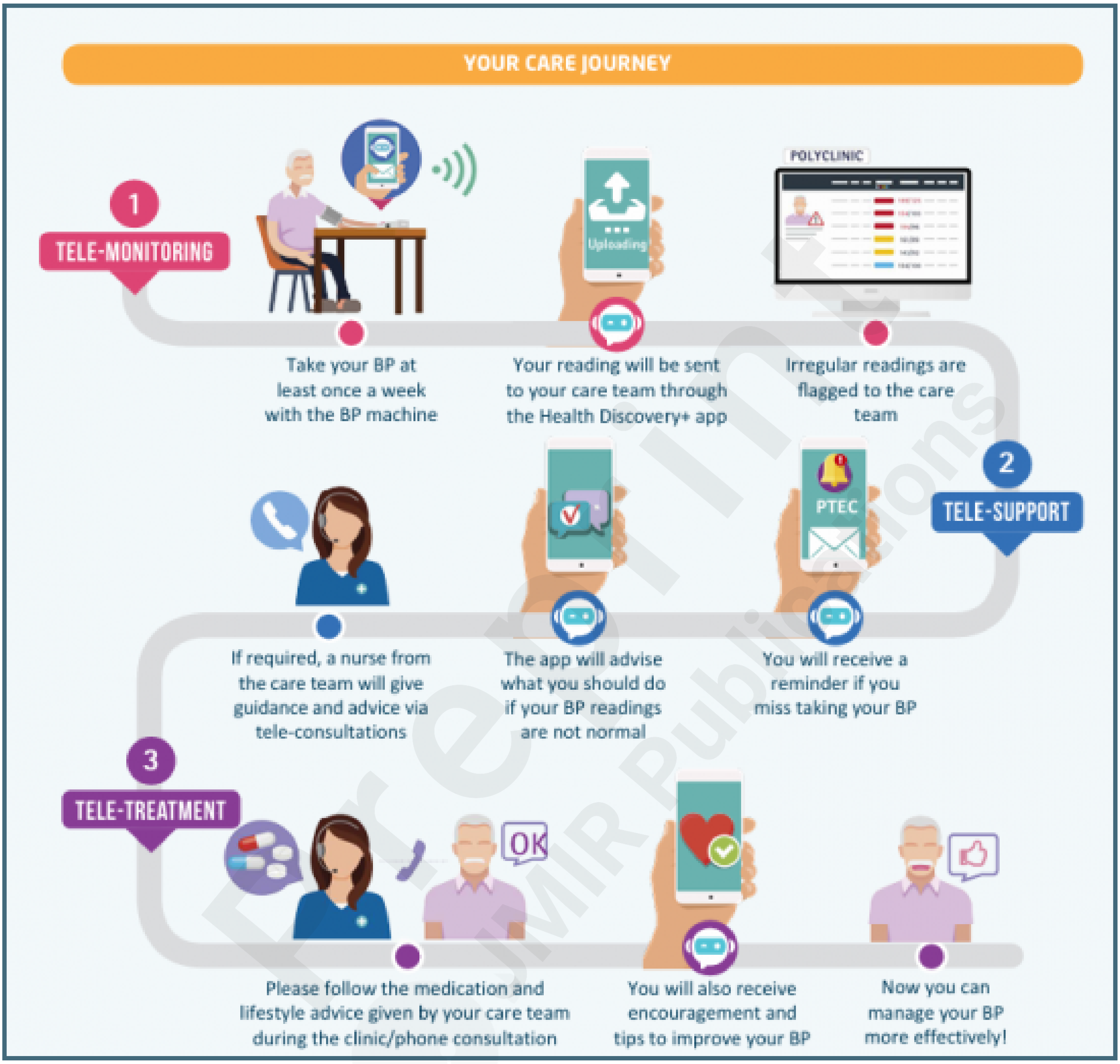
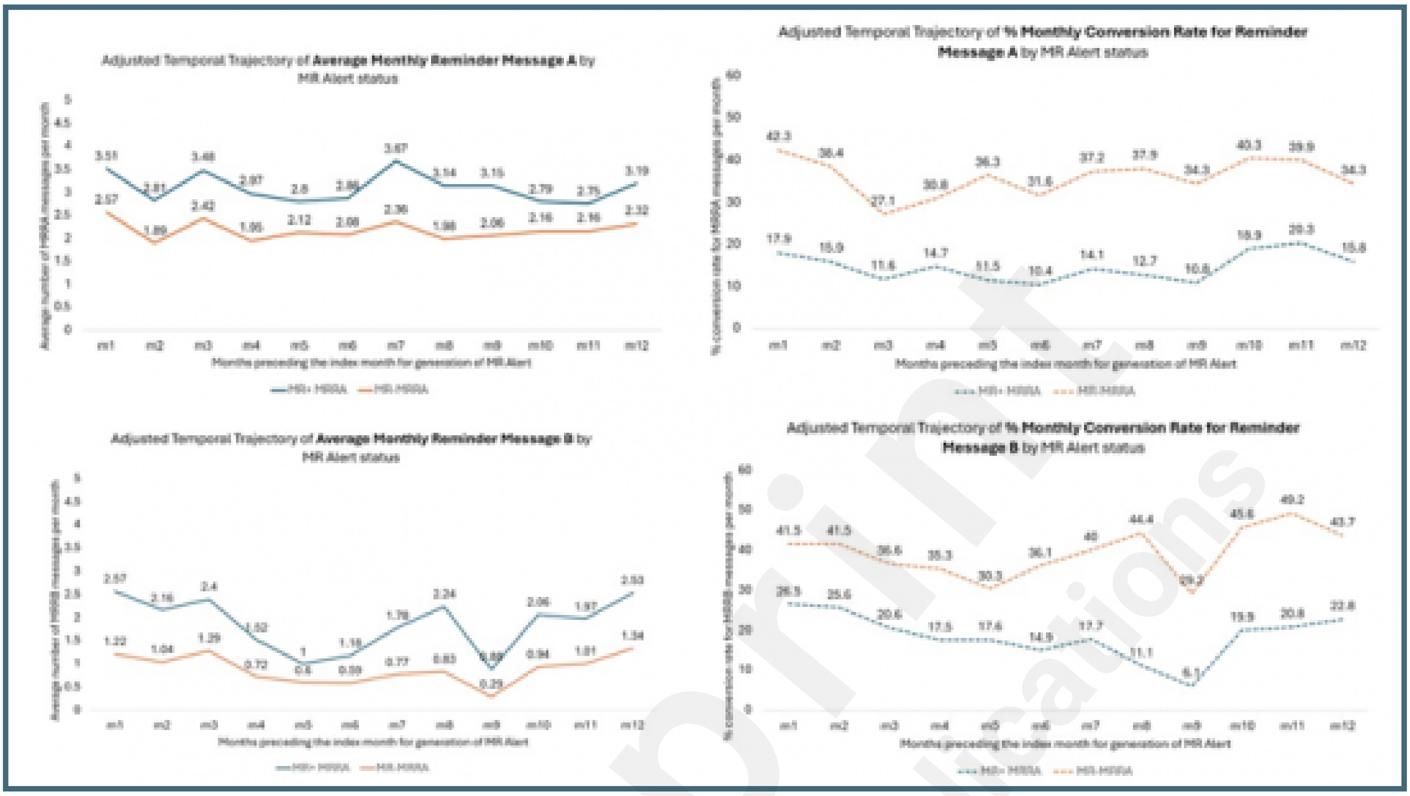
Supplementary Files

Figures

Patient Care Workflow or Journey within the PTEC-HT Scaling Program.



Adjusted temporal trajectories of MRRA and MRRB message counts and associated conversion rates stratified by MR alert generation status.



Multimedia Appendixes

Operationalization of time-points of data extraction from PTEC-HT system.
URL: http://asset.jmir.pub/assets/f5995f0895aa40c92762e605fe1bcd1e.docx

Model Fit Indices Table.
URL: http://asset.jmir.pub/assets/e68d784c55b37d2a6b191c11a481b904.docx

Temporal trajectory of Missed Reading Reminder A (MRRA) messages over 12 months preceding the index month of generation of MR Alert.
URL: http://asset.jmir.pub/assets/42c7629fdf5852a590036f4a569b4843.docx

Temporal trajectory of conversion rate to Missed Reading Reminder A (MRRA) messages over 12 months preceding the index month of generation of MR Alert.
URL: http://asset.jmir.pub/assets/b4fe331844c4e3ddae7a66a9135f0bfb.docx

Temporal trajectory of Missed Reading Reminder B (MRRB) messages over 12 months preceding the index month of generation of MR Alert.
URL: http://asset.jmir.pub/assets/c4590709545f94ad83668108e8301c3e.docx

Temporal trajectory of conversion rate to Missed Reading Reminder B (MRRB) messages over 12 months preceding the index month of generation of MR Alert.
URL: http://asset.jmir.pub/assets/eccd449e057b69c358d80992334364cb.docx