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Application of Structural Equation Modelling to Predict Acceptance and Use of mHealth Interventions at the Design Stage

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Abstract: The health status of women and children is considered as a reflection of the present society and predictor for the future generations. Unfortunately, challenges due to poverty, inadequate resources, illiteracy and socio-cultural barriers contribute to poor health and high maternal and newborn mortality in the developing countries. To address some of these challenges, there are several mHealth initiatives seeking to exploit opportunities provided by over 90% mobile penetration. However, most of these interventions have failed to justify their value proposition to inspire acceptance and use. It is our contention that the observed low up-take of mHealth innovations require holistic approach to align the solutions to consumer needs and expectations. In this paper, we demonstrate how to apply structural equation modelling to predict acceptance and use of mHealth interventions in low-resource settings. To identify factors that influence acceptance and use of mobile-based solutions, ninety five randomly selected antenatal and postnatal women were invited to participate in formal discussions on how mobile phones can be used to enhance access to maternal and newborn care. Seventy nine participants filled out self-assessment questionnaire as a prestudy to evaluate how their reaction would predict post-implementation reactions formed on the basis of significant hands-on experience. Based on the discussions and the results of the pre-study, we identified key factors that influence acceptance and use of mHealth interventions in low-resource settings. These factors were configured into a conceptual model comprising of nine variables used to predict post-deployment acceptance (fit) and use of mHealth prototype named Mamacare. After deploying mamacare in a rural hospital, a cohort of seventy nine subjects were recruited into a longitudinal experiment that involved sending of targeted SMS alerts on appointment reminders, safe delivery, danger signs, nutrition, preventive care, and adherence to medication. The experiment was designed to allow a within-subjects comparison in order to examine how structural equation modelling can be used to predict likelihood of acceptance and use of Mamacare based on reactions taken during the prestudy. After analyzing the prestudy dataset using SmartPLS, the results predicted 80.2% acceptance and 63.9% likelihood of use. However, results obtained from the first post-deployment user experience revealed lower rates of Mamacare acceptance and use at 69.1% and 50.5% respectively. The difference between prediction and actual outcome necessitated improvement of Mamacare using reactions obtained from the first post-test evaluation. Three months later, we conducted a follow-up post-test that recorded further drop in the acceptance from 69.1% to 60.3% but improved usage from 50.5% to 53.7%. Despite this variations, the study demonstrated that structural equation modelling is crucial to predicting acceptance and use of mHealth interventions in the early design stage.

Keywords: Behaviour science; design science; mHealth; partial least squares; post-deployment; predictive modelling; prototype; structural equation modelling; utilization.

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1. INTRODUCTION

To exploit vast opportunities provided by mobile penetration [1] in developing countries, there are several mHealth initiatives most of which are pilot projects in Sub-Sahara Africa and South Asia. However, due to fragmentation and mismatch to consumer needs, most of these initiatives have failed to address real healthcare challenges in low-income countries [2-5]. In fact, a global observatory survey conducted by WHO and International Telecommunication Union (ITU) in 64 developing countries revealed that only 9-16% of the countries have managed to implement eHealth systems without relying on donor funding [6]. We argue that, the poor uptake of mHealth is due to poor design strategies that are based on perceived problems rather than the reality in the intended context of use.

In order to accelerate seamless integration of mHealth into healthcare system, there is need for structured approach to predict acceptance (fit) and use of mHealth interventions at the design stage [7-8]. This study demonstrates how to apply structural equation modelling (SEM) to predict acceptance and use of mHealth solutions during the early design stage. Furthermore, the proposed approach is anchored on socio-technical dimensions of people, process, and technology that influence adoption of new technologies in the healthcare ecosystem. To identify key factors that influence acceptance and use of mHealth artefacts, we used focus group discussions (FDGs) in which selected patients, healthcare providers, software developers, and policy makers were involved. Feedback from these stakeholders together with meta-analysis of behaviour science and technology adoption theories formed the basis for the proposed theoretical model unveiled in the next section.

2. THEORETICAL FOUNDATION

To solve problems using information and communication technology (ICT) solutions, Hevner *et al.* [9] proposed a framework that integrates behavioural theories into design science. The framework is instrumental in development of ICT solutions that satisfies people's needs and expectations [10]. In addition to Hevner's framework, we reviewed several behaviour science and technology adoption models that are relevant to this study. These include Technology Acceptance Model (TAM) [11], Process Virtualization Theory and Impact of Information Technology (PVT-IT) [12], Task-Technology Fit (TTF) [13], and Theory of Planned Behaviour (TPB) [14]. Based on empirical findings from these models, we derived a theoretical model named **TIPFit**. The word TIPFit is an acronym derived from Technology, Individual, Process and Fit as shown in Figure 1. The three main components are further decomposed into variables used to predict acceptance and use of mHealth artefacts in maternal and newborn healthcare (MNH).

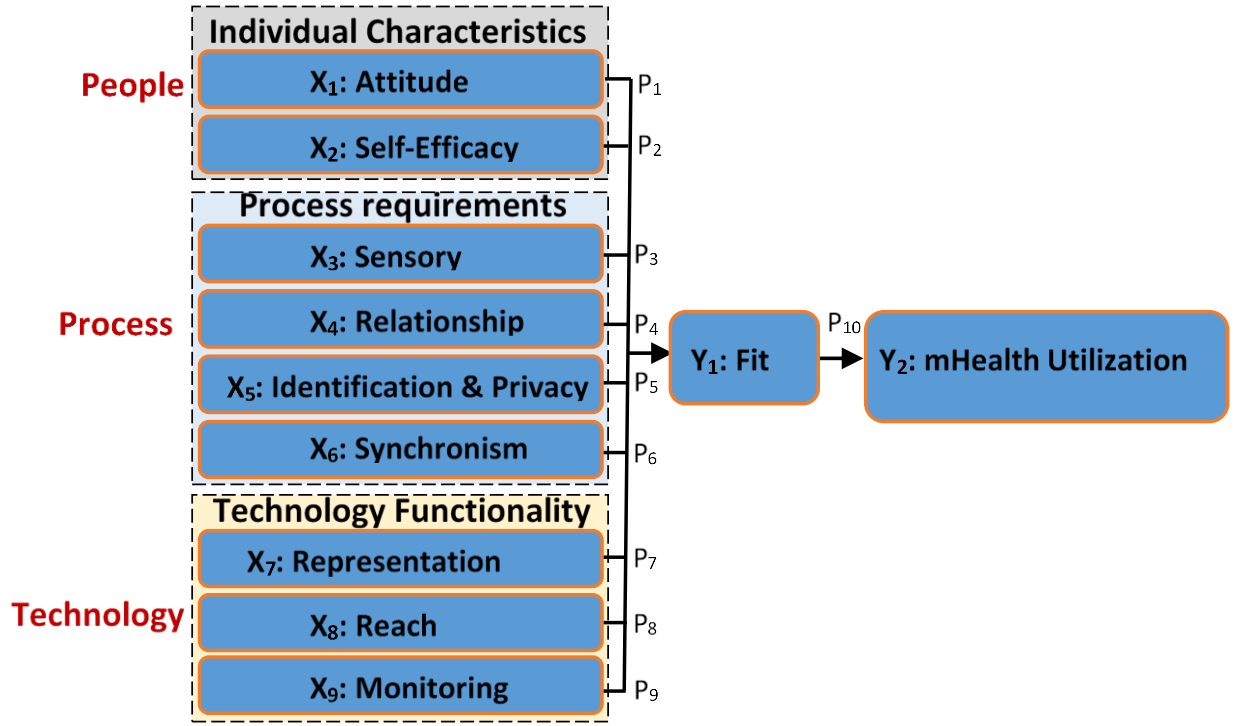


Figure 1: TIPFit model consisting of variables posited to influence acceptance (fit) and use of mHealth intervention.

2.1 Description of TIPFit Model

TIPFit model consolidates best practices in the field of design science in order to align technology to people and clinical processes. In the following section, we justify the configuration of TIPFit model that comprises of nine predictor variables posited to influence fit and utilization of mHealth solutions in low-resource settings:

- **Attitude:** This variable derived from TPB model is suitable for investigating one's judgment on certain behaviour, subject or action [14-16]. Inclusion of Attitude in the model was informed by a pre-study feedback that revealed attitude is key to acceptance of new technology innovations. Positive attitude may be influenced by perceived benefits while negative attitude may be due to unfavourable condition. We therefore argue that attitude is crucial in measuring intended users' perception before and after exposure to technology interventions.
- **Self-Efficacy:** Self-efficacy is derived from TAM and CSE models [11,17]. The construct is intended to measure individual's ability to use devices such as computers and mobile phones to access maternal care services and information. In this study, we employed design thinking to identify factors that influence usability of mHealth artefacts. In particular, we investigated one's ability to use a mobile phone to access maternal care services in low-resource settings.
- **Sensory requirements:** Sensory requirements derived from PVT-IT [12, 18, and 19] refers to the sense of touch, smell, sight, taste, and aural that may be important in clinical processes such as diagnosis. For example, during routine maternal care visits, clinicians use medical devices to physically capture clinical tests such as temperature, blood pressure, blood sugar, urinalysis, and

haemoglobin. Although some of these vitals may be captured remotely using biosensors, it may be difficult to deploy such technologies in low-resource settings [20]. This is why sensory requirements is critical in determining the degree to which low-cost mobile phones and point-of-care devices may be used to fulfil sensory requirements in clinical processes.

- *Relationship*: Relationship is derived from PVT-IT [12,18-20] to investigate degree of interaction between the caregivers and patients in a virtual environment. In clinical processes, relationship is important because it builds mutual trust between patients and healthcare providers. In a physical encounter, verbal and non-verbal communications convey vital information resulting to mutual trust and better inter-personal relationship.
- *Identification and privacy*: Identification refers to proof of one's identity while privacy refers to confidentiality of health information. This construct was derived from PVT-IT models [12, 18-20]. In clinical processes, fulfilling these requirements is essential if patients and caregivers are to share sensitive health information. For example, a HIV positive client may be unwilling to receive SMS alerts on adherence to antiretroviral (ARV) regimen. On the other hand, clinicians may be reluctant to perform diagnosis and prescription electronically to avoid compromising patient's privacy.
- *Synchronism*: In this context, synchronism is the degree to which activities that make up a clinical process need to occur with minimal delay [12, 18-20]. Synchronism is crucial in cases like preeclampsia that require urgent attention. In normal practice, these complications are mostly identified when a patient goes to hospital for routine check-up. These delays contribute to maternal and newborn deaths which could have been avoided if mechanisms for early detection are established. Synchronism was used to investigate the degree to which an intervention would reduce delays in seeking maternal services and information through use of mobile phones and point-of-care devices.
- *Representation*: Representation derived from PVT-IT [12, 18-20] refers to the capability of information technology to replicate a physical process or object. Due to complexity of clinical processes, we argue that difficulty of replicating processes such as treatment may be one of the reasons for low uptake of mHealth interventions. Using TIPFit model, we investigated degree to which representation could be realized using cost-effective mobile telemedicine products.
- *Reach*: This construct was adapted from PVT-IT [12,18-20] to measure capability of technology to provide sufficient access to maternal and newborn care services at reduced cost, time and distance of travel. Reviewed case studies indicate that most mHealth interventions fail to provide sufficient access to care services due to limited resources and infrastructure [18]. In this study, we used TIPFit model to investigate how mobile phones and low-cost medical devices could provide sufficient reach by reducing time and cost of accessing maternal care and information in low-resource settings.

- *Monitoring*: Monitoring was adapted from PVT-IT [12, 18] to measure capability of technology to effectively and efficiently monitor maternal and newborn's health condition. During antenatal and postnatal care, mothers are required to make regular visits to hospital for constant monitoring. However, some women fail to honour such visits resulting in complications such as hemorrhage due to hyperglycaemia. This study used TIPFit to investigate how portable point-of-care devices and mobile phones could be used to provide sufficient monitoring of maternal and newborn health status.
- *Fit*: Refers to acceptance or perception on suitability of mHealth intervention in fulfilling client's needs and expectations [18, 21]. Fit is an intervening variable implying that the higher the perceived fit, higher will be the likelihood of utilizing mHealth intervention.
- *mHealth Utilization*: In this context, utilization refers to making practical and worthwhile use of mHealth products and services. This variable is used to predict adoption and sustainable use of mHealth solutions during the design phase [22].

3. RESEARCH METHODS

3.1. Mamacare Prototype Development Process

To demonstrate practical utility of TIPFit model, we operationalized it into blueprints for the design and implementation of mHealth prototypes. The blueprints were used in a user-centred design to conceptualize, design, build, and deploy a maternal care prototype known as Mamacare. The word Mamacare is derived from two words, i.e., *mama* that stands for “mother” and *care* which in this context stands for maternal and newborn healthcare. Table 1 shows how the model constructs were mapped onto workflows that guided development of Mamacare prototype.

Table 1: Extract of blueprint derived from TIPFit model used in development of Mamacare

Concept	Conceptualize*	Design	Build	Deploy
Attitude	Use strategies e.g. creative thinking and field surveys to formulate solution to the problem. Test user's attitude to predict acceptance and use	mHealth physical designs should be based on explicit understanding of target through participatory design approaches	Involve stakeholders where possible during implementation. This may be achieved through piloting and release of beta versions	During deployment, conduct training and support. Also administer user acceptance tests to evaluate utilization and user satisfaction.
Self-Efficacy	Investigate individual's ability and competences in using computers and mobile devices. Pretest self-efficacy to predict utilization	Responsive design to enhance user experience. Use mock-ups to get optimal content and navigation presentation	Use rapid development toolkits to implement mHealth artefacts that are responsive to user and device profiles.	Evaluate user's feedback on perceived ease of use. Feedback used to enhance user interface and content representation

To improve access to maternal care services, Mamacare sends text alerts on clinic appointment, danger signs, safe delivery, nutrition, preventive care, and adherence to medication using SMS protocol as shown in Figure 2. On the web portal, the system receives data on vital signs such as blood pressure, temperature, haemoglobin and blood sugar captured using low-cost point of care devices. For ease of processing antenatal, delivery, and postnatal health records, a workstation installed in the hospital has a secured web portal that is only accessible to caregivers depending on assigned roles and privileges.

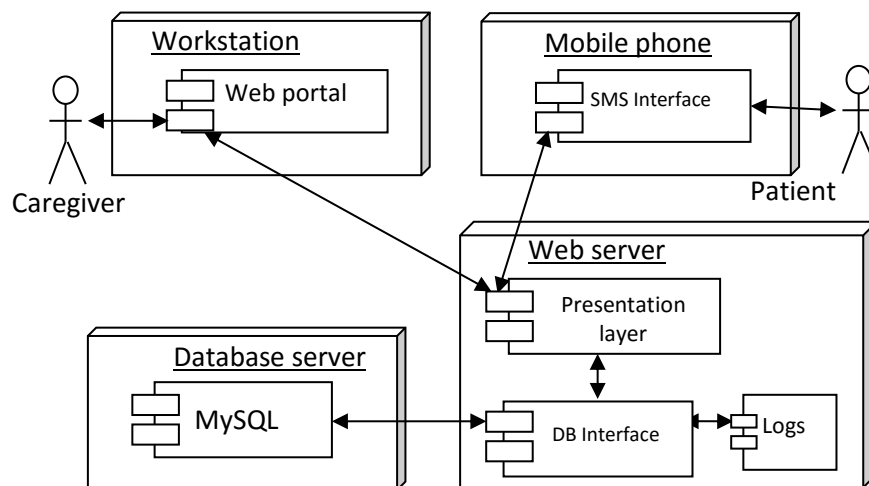


Figure 2: Mamacare conceptual design. Client-side consists of mobile web interface for caregivers and SMS interface for the patients.

To enhance user experience, Mamacare web portal was implemented using responsive design to dynamically adapt to multiple device profiles depending on the viewport and processing power of the execution environment. Figure 3 shows how the same page used to manage maternal client's records appear on a desktop computer and low-end mobile phone.



Figure 3: Mamacare web portal on computer and mobile phone interface on the right. The portal dynamically adjusts to fit onto any portable device viewport.

3.2 Hypotheses for Predicting Acceptance and Use

In predictive modelling, a linear regression or neural network models may be used to predict future outcome based on input from past and current events. In this study, we operationalized TIPFit constructs into a set of hypotheses that were tested using the following structural equation model:

$$Y_j = \beta_i X_i + \epsilon_i \quad (\text{where } i = 1 \dots 9; \text{ and } j=1,2)$$

In the equation, X_i represents predictor variables on TIPFit model that are hypothesized to influence “fit and utilization outcomes” represented using Y_j . The term β_i represents path coefficients used to determine the effect of each predictor variable on fit. The error term in the equation, i.e., ϵ_i represents random variation from unexplained factors that influence fit and utilization of mHealth artefacts. Table 2 shows the set of hypotheses used to determine the effect of the nine predictor variable on fit. The path coefficient represented by P_{10} is used to measure the effect of fit (Y_1) on mHealth utilization (Y_2).

Table 2: Hypothesized relationships between variables TIPFit model variables

Path	Hypothesis
P ₁	Attitude towards technology has no significant effect on fit of mHealth intervention
P ₂	Self-efficacy on using mobile devices or computers has no significant effect on fit of mHealth intervention
P ₃	Sensory requirements of touch, sight and aural experience have no significant effect on fit of mHealth intervention.
P ₄	Relationship requirement between patient and caregiver has no significant effect on fit of mHealth intervention
P ₅	Identity and privacy requirement between patient and caregiver has no significant effect on fit of mHealth intervention
P ₆	Synchronism requirement of time-constrained processes has no significant effect on fit of mHealth intervention
P ₇	Representation capability of mHealth artefact has no significant effect on fit
P ₈	Reach capability of mHealth artefact has no significant effect on fit
P ₉	Monitoring capability of mHealth artefact has no significant effect on perceived fit
P ₁₀	Fit has no significant effect on utilization of mHealth artefact in low-resource settings

3.3 Repeated Measures Experiment

For a period of six months, we conducted repeated measures experiment in which data was collected using indicators derived from each construct of TIPFit model. For each indicator, a set of at least three likert-type questions on a scale of 1-5 were used. During the first month after recruiting the subjects, the pretest questionnaire was used to predict Fit and utilization of mHealth in MNH. Figure 4 shows the research design from prediction phase to post-tests (confirmatory phase) after subjecting the study cohort to the experimental treatment.

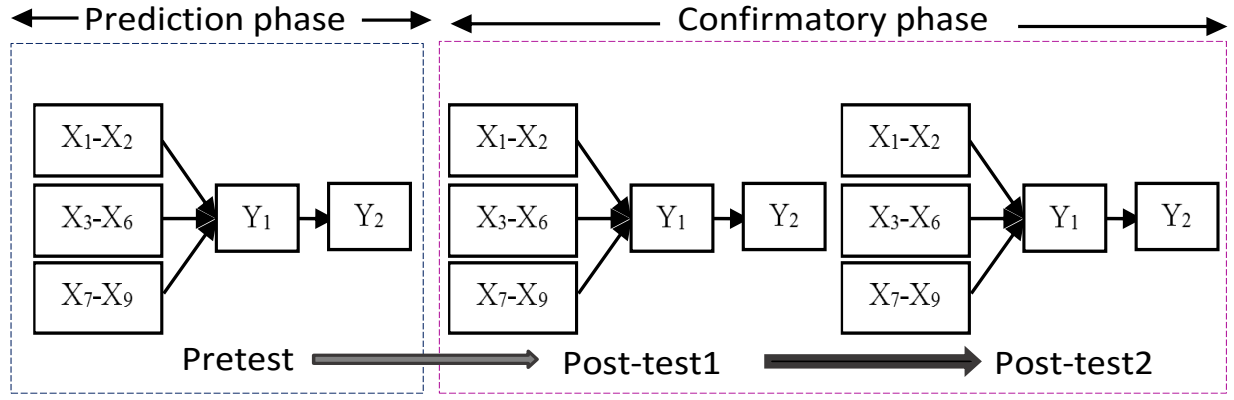


Fig. 4. Experiment to predict acceptance and use of mHealth interventions in low-resource

The first post-test was conducted three months after exposing the subjects to the treatment. Later, another post-test was conducted after six months into the experiment using the same tools employed in the first post-test. The reason behind the time lag between the tests was to minimize crossover effect that is common in within-subjects experimental designs.

3.4 Sampling and Inclusion Criteria

To get a representative sample, we used stratified random sampling based on education level, gravidae, age, residence, ethnicity, and ownership of a mobile phone. The sample frame comprised of 226 women registered for antenatal and postnatal in rural hospital located 110km from Nairobi. Using Cohen [24] recommendations, we used the following formula to obtain the optimal sample size:

$$n = \frac{1.96^2 \times 0.02 \times 0.98 \times 226}{0.02^2 (226 - 1) + 1.96^2 \times 0.02 \times 0.98} = 102$$

However, due to limitations imposed by the inclusion criteria, ninety five participants were invited through SMS and voice calls, but seventy five of them agreed to participate in the six-month experiment.

4. RESULTS FROM STRUCTURAL MODEL AND DISCUSSION

4.1 Characteristics of the Study Cohort

Demographic attributes such as gender, age and education level may be used to determine individual's belief, attitude and ability to perform tasks using technology [25]. For this reason, we first analysed the age and education levels of the study cohort. Figure 5 shows demographic details obtained from 73 valid responses obtained from the cohort of 79 subjects. The chart on the left indicates that 64% of the subjects were women aged between 15 and 25 years while that on the right shows distribution of their education levels.

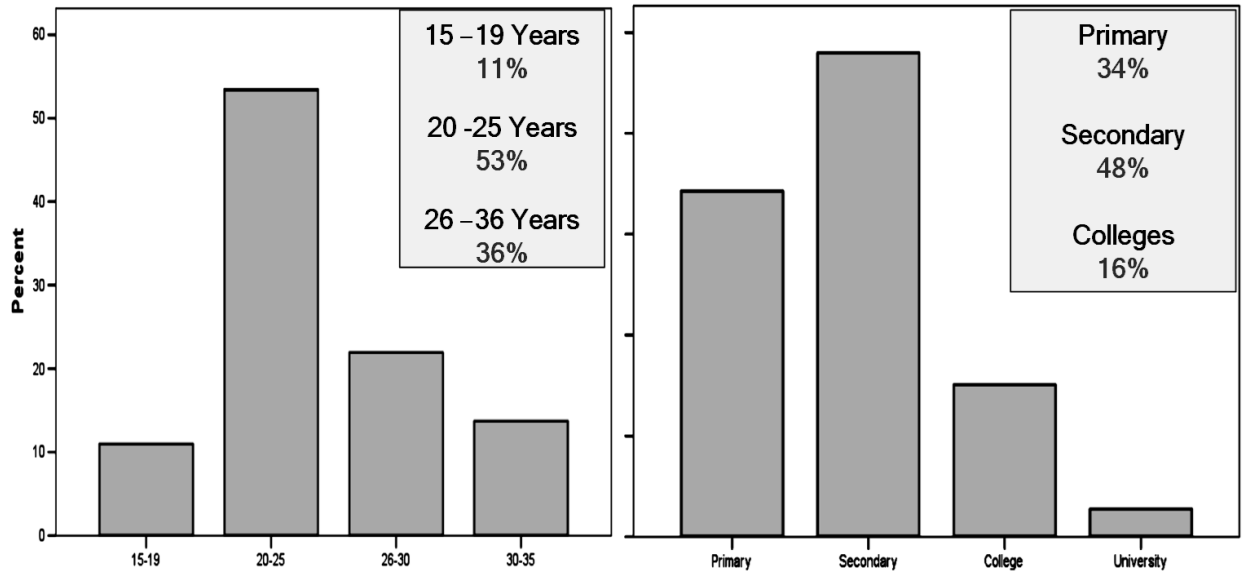


Figure 5: Demographic details of 73 valid responses from 79 subjects who participated in the pre-study at Kimbimbi Sub-County Hospital in Kenya.

4.2 Reliability and Validity Tests

To test reliability of the model, we used composite reliability and Cronbach's alpha tests available in SmartPLS [26]. Figure 6 shows a chart generated from the pretest dataset with all the model constructs scoring above 0.70. Similarly, reliability test from the two post-test datasets demonstrated high internal consistency. Further, we tested the pretest and post-test models for convergent, and discriminant validity using Average Variance Extracted (AVE). For each of the models, all the constructs scored values above 0.50, i.e., 50% hence, demonstrating good convergent and discriminant validity [27].

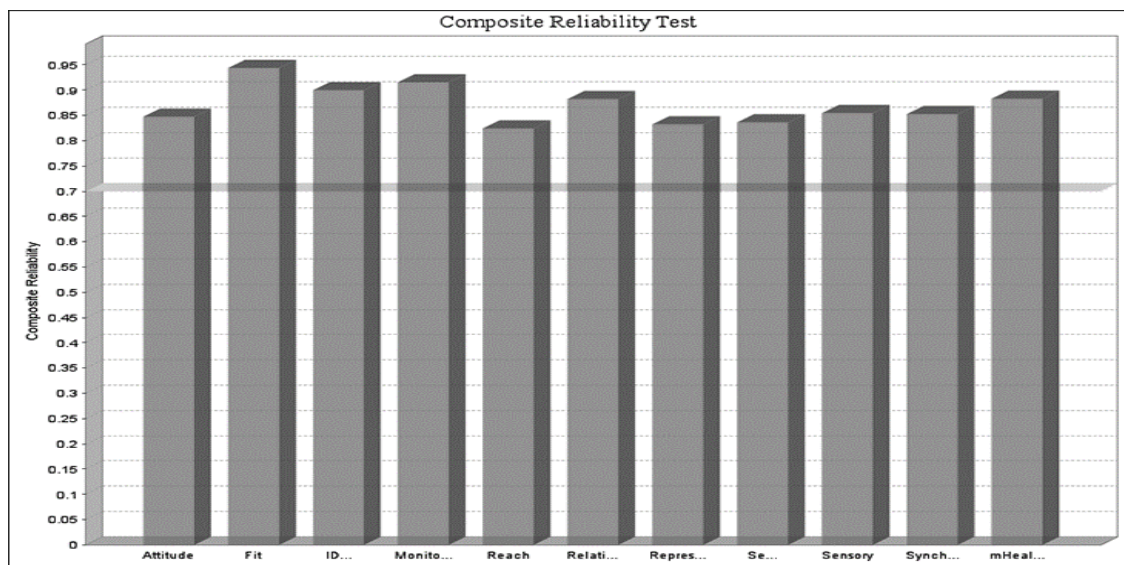


Figure 6: Reliability test of the pretest model. The constructs scored above 0.7 threshold

4.3 Structural Modelling of Pretest and Post-test Models

Once the pretest and two post-test datasets passed the reliability and validity tests, we

proceeded to the next step of creating the graphical models using the design tools available in SmartPLS. In this section, we provide the results of analyzing the graphical models obtained from the three datasets.

4.3.1 Path Analysis of Pretest Dataset

To predict acceptance and use of Mamacare in the low-resource settings, we used SmartPLS to generate the graphical model shown in Figure 7 from the pre-test dataset. The measurement model shows the factor loadings generated from manifest variables (boxes labelled Q2.1 to Q12.2); while the structural model depicts the path weights and coefficient of determination (R^2) for fit and mHealth utilization. The R^2 of 0.802 and 0.639 generated from the pretest dataset indicates that TIPFit has high predictive power of 80.2% on fit and 63.9% probability of use.

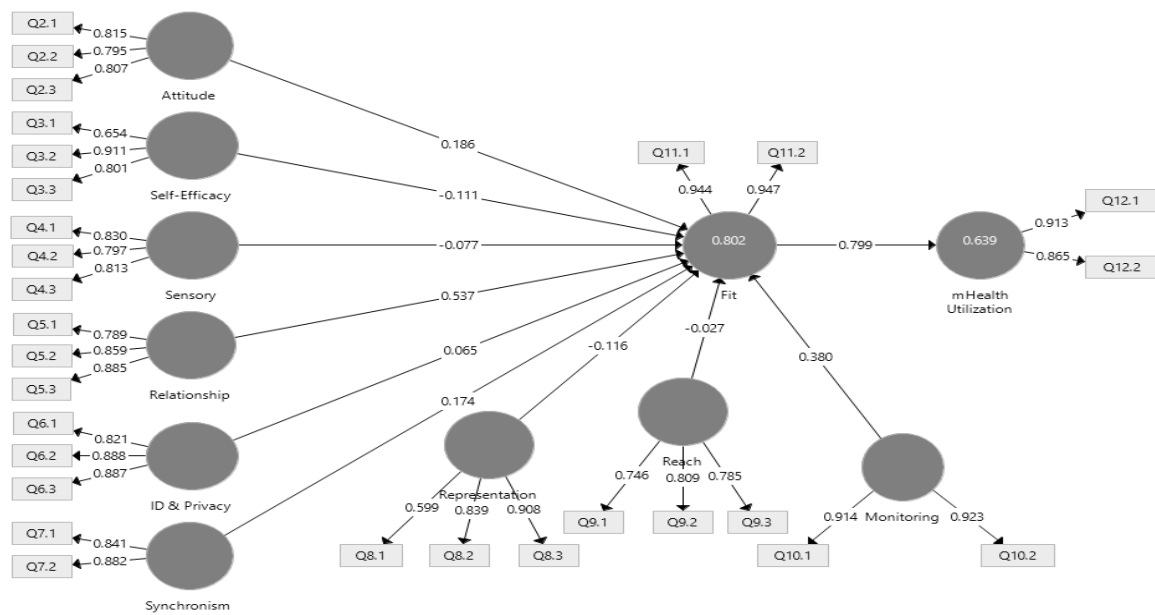


Figure 7: Computed model generated from pretest dataset to predict acceptance and utilization of mHealth amacare

4.3.2 Path Analysis of Post-tests Datasets

The same approach was used to generate graphical models from the two post-test datasets collected after subjecting the study cohort to mamacare intervention. Results from the first post-test registered R^2 of 69.1% on fit and 50.5% rate of actual use. These low scores necessitated improvement of Mamacare based on feedback obtained from caregivers and the study cohort during the first post-test evaluation. It is after these improvements on features and functionalities of Mamacare that we conducted the second post-test. The results revealed there was marginal decline in fit at R^2 of 60.3% but improved use from 50.5 to 53.7%. Overall, Table 3 gives a summary of the path weights generated from the three datasets.

Table 3. Path weights generated from pretest and post-test datasets using SmartPLS

	Attit	Self	Sense	Relat	Priv	Sync	Rep	Reach	Mon	Fit.
Pretest	0.19	-0.11	-0.08	0.54	0.07	0.17	0.12	-0.03	0.38	0.79
Post1	0.21	-0.06	-0.15	0.08	0.20	0.13	0.31	0.24	0.02	0.71
Post2	0.22	0.01	-0.18	-0.04	0.19	-0.02	0.15	0.29	0.26	0.73

4.3.3 Consolidated Pretest and Post-test Models

Further, we collapsed the model into its abstract view to measure the overall effect of the main constructs namely individual characteristics, process requirements, and technology functionality on fit. Figure 8 shows consolidated pretest model with factor loading from each predictor variable, path weights, and R^2 of 66.9% on fit and 60.7% rate of Mamacare use.

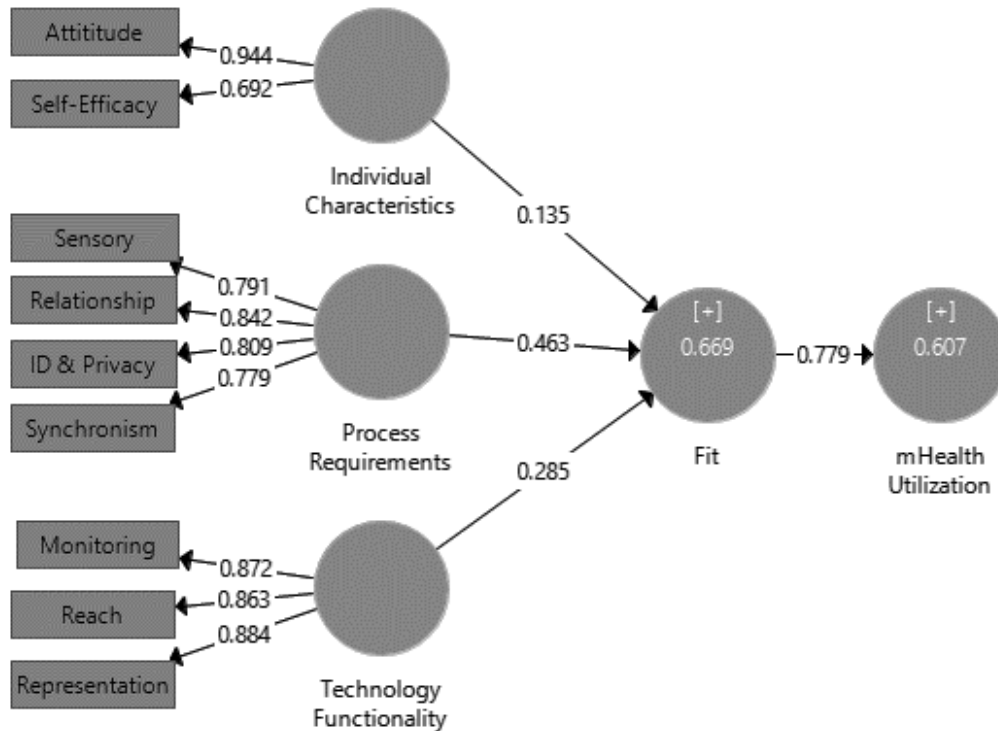


Figure 8: Modeling main constructs used to predict fit and utilization before deployment of Mamacare

To determine significance of path coefficient for each of the three main constructs, we used bootstrapping algorithm in SmartPLS. Table 4 shows that the pretest predicted that the process requirements construct has the strongest effect on fit.

Table 4: Summary of path weights, t-statistic, Effect size and p-value of the prediction model

Main construct	Path β	t-value	Effect- f^2	p-value	Remarks
Individual Characteristics	0.135	2.053	0.024	0.0439	Small significant effect
Process Requirements	0.463	3.007	0.233	< 0.001	Large significant effect
Technology Functionality	0.285	2.695	0.073	0.008	Small significant effect
Fit ->Tech. utilization	0.779	20.297		< 0.001	Large significant effect

To compare the predictive power of the main constructs, we consolidated the two post-test datasets to generate the composite model shown in Figure 9. The post-intervention model returned R^2 of 60% on fit compared to 66.9% of the pretest model. However, the consolidated pretest and

post-test graphical models shows that there was a huge disparity between predicted use of 60.7% and the actual use of 47.6%. This outcome necessitated use of alternative techniques discussed in the next section in order to draw reliable conclusions.

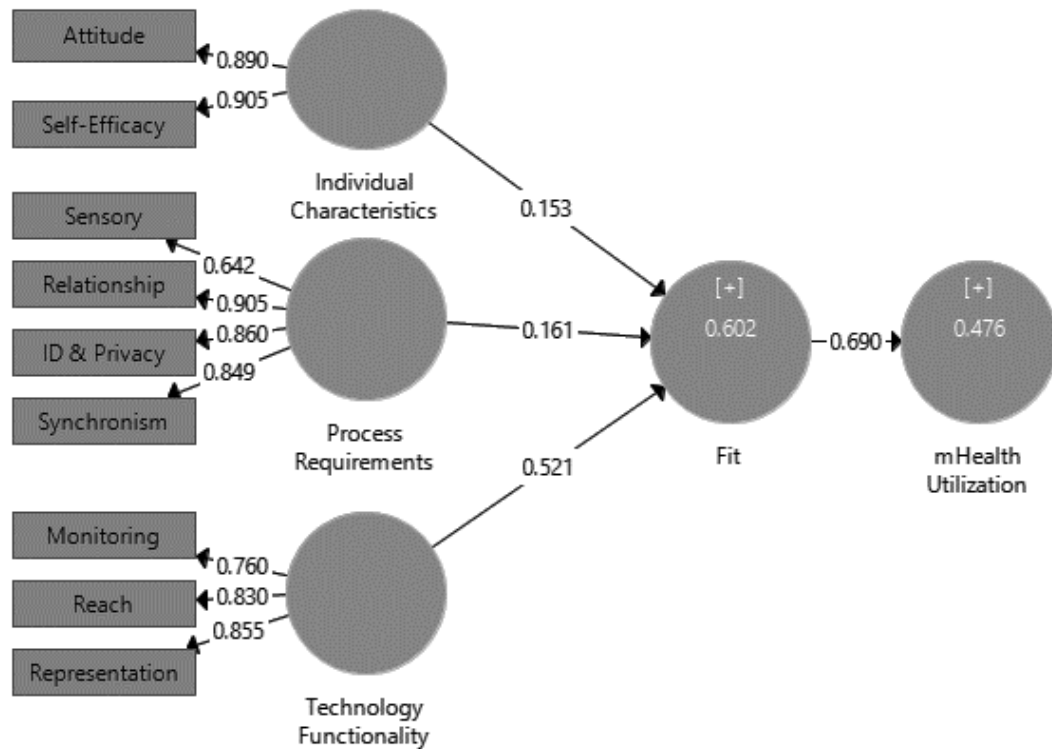


Figure 9: Composite post-test model used to evaluate fit and actual use of Mamacare prototype

Table 5 gives a summary of the path weights, t , f^2 and p values after subjecting the model to bootstrapping algorithm. Contrary to the pretest findings, the post-test model shows that technology functionality has the strongest effect on fit.

Table 5: Summary of path weights, t -statistic, Effect size and p -value of composite post-

Main Construct	Path β	t -value	Effect- f^2	p -value	Significance
Individual Characteristics	0.153	2.828	0.025	0.006	Small significant effect
Process Requirements	0.161	2.776	0.020	0.007	Small significant effect
Technology Functionality	0.523	10.041	0.236	< 0.001	large significant effect
Fit ->Tech. utilization	0.690	16.396		< 0.001	Large significant effect

To determine the impact of Mamacare intervention, we compared the pretest and post-test models. In this section, we used the results from the graphical models and parametric tests to draw reliable inference on the set of hypotheses stated earlier in Table 2.

4.4 Significance of Structural Model Path Weights

To test significance of the path weights, we used bootstrapping algorithm in SmartPLS to determine significance of path coefficients using Student's t test at 5% significance level. Table 6 gives a summary of t values obtained after bootstrapping the path weights from the pretest and the two post-test models.

Table 6. Significance of pretest and post-tests path coefficients

	Attit	Self	Sense	Relat	Priv	Sync	Rep	Reach	Mon	Fit
Pretest	2.38	-1.71	-1.79	5.07	0.75	2.28	1.43	-0.37	2.73	20.48
Post1	2.96	-0.83	-3.53	1.09	3.40	1.30	3.91	5.09	0.30	19.52
Post2	3.16	0.08	-3.65	-0.59	2.14	-0.25	1.94	3.64	3.86	20.39

The results from the table shows that attitude towards fit was significantly positive before, and after intervention. Although effect on Self-Efficacy was insignificant before and after intervention, there was improvement after subjecting the cohort to Mamacare Intervention. Nevertheless, effect of Fit on mHealth utilization was highly significant before and after intervention. In terms of process requirements, effect of sensory as predictor of fit was consistently negative before and after intervention. However, inspection on the path weights from the three datasets shows some inconsistencies in synchronisms, representation, and monitoring. To investigate the overall effect of the three main constructs, we compared path coefficients, t, p and effect size of the composite pre-test and post-test models as shown in Table 7.

Table 7: Comparison between the pretest and post-test path weights, t-statistic, Effect size and p-

Main Construct	Pretest model				Post-test model			
	Path β	t	p	Effect size f^2	Path β	t	p	Effect size f^2
Individual Characteristics	0.135	2.053	0.0439	0.024	0.153	2.828	0.006	0.025
Process Requirements	0.463	4.736	< 0.001	0.233	0.161	2.776	0.007	0.020
Technology Functionality	0.285	2.695	0.008	0.073	0.523	10.041	< 0.001	0.236
Fit ->Tech. utilization	0.779	20.297	< 0.001		0.690	16.396	< 0.001	

The table shows that before exposure to Mamacare intervention, the model predicted that process requirements construct has the highest effect on perceived fit. However, after exposing the subjects to Mamacare intervention, the dimension on technology functionality recorded the highest effect on fit while individual characteristics remained relatively constant. Inference on hypothesized relationship between fit and mHealth utilization revealed that fit of mHealth intervention was positive and highly significant before and after Mamacare intervention. However, due to notable inconsistencies in some predictor variables hypothesized to influence fit, we subjected the three datasets to parametric tests using SPSS discussed in the next section.

4.5 Parametric Analysis using Repeated Measures ANOVA

Due to inconsistencies observed in the structural models, we found it necessary to subject the datasets to parametric tests that draw inference from variance (δ^2) and population mean (μ) [27]. However, before we subjected the three datasets to parametric tests, we tested each for outliers, sphericity and normal distribution. Although the tests showed that the sample means were normally distributed, there were minor violations of sphericity. To correct these violations, we used Greenhouse-Geisser (GG) algorithm in order to use Repeated Measures ANOVA (RM-ANOVA).

Table 8 shows the results of sphericity (χ^2 and p), RM-ANOVA (F and p), and Effect size (Eta²).

Table 8. Test of overall treatment effect using Repeated Measures ANOVA

Predictor Variable	Sphericity		ANOVA:		Effect	Remarks
	χ^2	p	F	p	Partial Eta ²	Greenhouse-Geisser Correction (GGC)
Attitude	0.534	0.766	2.595	0.078	0.036	Not significant
Self-Efficacy	3.432	0.180	3.258	0.041	0.045	Significant
Sensory requirements	5.109	0.078	1.233	0.295	0.018	Not significant
Relationship	22.076	<0.001	4.038	0.029	0.055	GGC used: significant
Identification and Privacy	9.980	0.007	7.462	0.001	0.098	GGC used: significant
Synchronism	13.683	0.001	8.022	0.001	0.104	GGC used: significant
Representation	10.664	0.005	2.373	0.105	0.033	GG: Not significant
Reach	5.034	0.081	1.117	0.330	0.016	Not significant
Monitoring	20.082	<0.001	13.384	<0.001	0.162	GGC used: significant
Fit	8.516	0.014	10.144	<0.001	0.128	GGC used: significant
mHealth Utilization	1.350	0.509	4.152	0.018	0.057	Significant

Inspection on p and F values from the table revealed that the experimental treatment had significant effect ($p < 0.05$) on seven out of the eleven TIPFit constructs. These are self-efficacy, relationship, identification and privacy, synchronism, monitoring, Fit and mHealth utilization. Further analysis of the three datasets using Bonferroni pairwise comparisons between the pretest and the two post-tests is provided in Table 9. The results are tabulated in terms of sample mean ($\bar{x} = \mu$), Standard Error (SE) and p values calculated from differences between sample means of the pretest (T_0), post-test1 (T_1) and post-test2 (T_2) datasets.

Table 9. Comparison between means using Bonferroni post-hoc test

Predictor Variable	Pretest		Post-test1		Post-test2		Mean differences		
	$\bar{x} = \mu$	SE	$\bar{x} = \mu$	SE	$\bar{x} = \mu$	SE	$T_0 - T_1$	$T_1 - T_2$	$T_0 - T_2$
Attitude	1.56	0.06	1.39	0.06	1.54	0.06	0.11	0.17	0.99
Efficacy	1.55	0.07	1.35	0.06	1.55	0.06	0.10	0.04*	1.00
Sensory	2.23	0.12	1.98	0.12	2.11	0.08	0.05*	0.21	0.39
Relation	1.81	0.09	1.53	0.06	1.66	0.06	0.11	0.17	0.99
ID & Privacy	1.89	0.09	1.51	0.07	1.58	0.06	0.01*	0.86	0.01*
Sync	1.84	0.10	1.43	0.07	1.61	0.06	0.00*	0.09	0.09
Represent	1.63	0.07	1.47	0.06	1.52	0.05	0.11	0.83	0.48
Reach	1.74	0.07	1.59	0.08	1.65	0.06	0.47	0.93	0.64
Monitor	1.66	0.08	2.00	0.00	1.60	0.06	0.00*	0.00*	0.92
Fit	1.77	0.09	1.36	0.06	1.54	0.06	0.00*	0.06	0.06
Use	1.69	0.08	1.43	0.07	1.51	0.06	0.02*	0.74	0.18

The table shows there are significant differences between the pretest and first post-test ($T_0 - T_1$) in six TIPFit constructs. Between the first and second post-test ($T_1 - T_2$), there were significant differences in two variables, i.e., Self-Efficacy and mHealth Utilization. Surprisingly, comparison between the pretest and second post-test ($T_0 - T_2$) shows the only significant difference was in identification and privacy construct. This may be interpreted to mean that after improvement of Mamacare, it was possible to satisfy needs and expectations expressed during the pretest evaluation. This confirms Davis and Venkatesh [28] assertion that evaluating user's behaviour and expectations during the early design stages of a new software system could provide valuable insights into its post-implementation acceptance and use.

5. CONCLUSION

In this study, we proposed a new approach to predicting acceptance and use of mHealth interventions using structural equation modelling. The pre-study fieldworks and review of related work gave us insight on factors that influence acceptance (fit) and use of mHealth interventions in low-resource settings. These factors were configured into a theoretical model used to predict acceptance and use of mHealth prototype named Mamacare deployed in a rural hospital. During the early design of Mamacare prototype, we conducted a pretest that predicted 80.2% fit and 63.9% likelihood of use. After recruiting 79 subjects for Mamacare intervention, the first post-test revealed fit of 69.1% and 50.5% actual use. However, the second post-test registered a marginal drop in fit from 69.1% to 60.6% but improved use from 50.5% to 53.7%. Despite some inconsistencies in predicting fit, findings from this study demonstrated that individual characteristics, process requirements, and technology factors have significant effect on fit (acceptance) and use of mHealth interventions in low-resource settings. Undoubtedly, success of mHealth in developing countries depends on how value is driven by aligning mHealth solutions to people and clinical processes in the early design phase.

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