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The development of an instrument to predict patients' adoption of mHealth in the developing world

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Abstract

Introduction: There are many tools for measuring patient's potential adoption of mHealth (i.e. mobile health) in the developed world, but none of these instruments provides a comprehensive means for measuring critical issues affecting the adoption of mHealth by patients in the developing world. The aim of this paper was to develop a valid and reliable assessment instrument for predicting mHealth adoption by patients in the developing world.

Method: A Patients mHealth Technology Adoption Questionnaire (PmTAQ) was developed based on themes identified through a prior published structured literature review of factors affecting patients' mHealth adoption in the developing world, from which eight constructs evolved. Face and content validity was confirmed by 15 mothers who had used mHealth (the Mobile Technology for Community Health (MoTeCH) service) for maternal care, and the findings were used to improve the instrument. To assess the validity and reliability of the instrument at least 64 mothers who used MoTeCH were randomly selected from each of nine clusters of health posts in one district in Ghana. The assessment instrument consisted of 39 items, categorised under eight components: Cost and ownership, user characteristics, language and literacy, infrastructure, collaboration and funding, governance, system utility, and intention to adopt. Exploratory and confirmatory factor analysis were performed.

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Authors' contributions
All authors jointly conceived the study, and jointly contributed to the design and development of the study tools. MAD performed the survey of the mothers, performed analysis, developed the model and wrote the first draft of the manuscript. MM and RES provided substantial editorial and intellectual input, and all authors contributed to subsequent re-visions. All authors approved the final manuscript.

Declaration of competing interest
The authors declare that they have no competing interests.

Consent for publication
Not applicable.

Availability of data and materials
Data available upon reasonable request.

Results: The data from 585 mothers were analysed. Exploratory factor analysis showed the eigenvalue of all eight components to be significant (cumulative total greater than 1.0). Bartlett's test of sphericity was significant, the Kaiser-Meyer-Olkin value was 0.84 and the mean Cronbach's α value was 0.82 (range 0.81–0.83). The components were found to be valid. Confirmatory factor analysis showed that all indices for the measurement model were within acceptable limit leading to the use of structural equation modelling to show the causal relationship between components, resulting in the development of the mHealth Adoption Impact Model (mAIM). The mAIM shows a strong relationship between latent constructs for patients' mHealth adoption.

Conclusion: The study presents an evidence-based, reliable and valid instrument and model for application in future research, policy development, and implementations related to patient mHealth adoption in the developing world.

Keywords

mHealth; Adoption; Patients; Assessment scale; eHealth; Telemedicine; Developing world

1. Introduction

mHealth, or mobile health, describes the delivery of health services using mobile devices such as mobile phones, smartphones, tablets, personal digital assistance and wearable devices [1]. It makes use of the services that are either already embedded in the mobile device (i.e., text messages, voice, multimedia) or supported by applications or accessories that bring additional functionality (e.g., remote sensors) [2]. mHealth supports healthcare delivery in a number of ways, such as the collection of clinical data [3,4], providing practitioners and patients with health services [5], supporting research and education [6,7], and providing real-time patient monitoring [8,9].

mHealth also offers cost-and-time effective services to all stakeholders in the healthcare delivery value chain, improving data collection [10], and radically extending and improving access to services for people living in resource-poor settings [2]. These benefits, coupled with increased availability of and connectivity for mobile phones in developing countries, have led many low-and-middle-income countries to invest heavily in mHealth [11,12]. This has made it possible for mHealth projects to be launched all over the developing world, mostly spearheaded by governments as a strategy to complement actions related to achieving Universal Health Coverage [13], meeting the health-related Millennium Development Goals, and now the Sustainable Development Goals [14]. However, while some projects have met their objectives, many did not progress beyond the pilot stage, or reach their full potential [15,16].

Several challenges account for this phenomenon in the developing world, such as failure in addressing issues of cost and ownership, user characteristics, language and literacy, infrastructure, collaboration and funding, governance, system utility, and non-existing or inappropriate assessment frameworks [15,17]. Among these is an increasing appreciation of the lack of an appropriate instrument to predict successful adoption before implementation [15]. Commonly used models for predicting the adoption of mHealth have been the

Technology Acceptance Model (TAM) [18], Unified Theory of Acceptance and Use of Technology (UTAUT)) [19], and their variants (TAM2, TAM3, UTAUT2). TAM and UTAUT are the two most widely used and cited instruments for predicting why potential users may accept or reject a given technology [20, 21]. However, even though they were originally designed to predict the behaviour of people who had previously used the technology [22], they have subsequently been used to predict the adoption of technology by potential rather than actual system users. Additionally, TAM and UTAUT were not originally developed for the assessment of healthcare systems but for explaining what factors were associated with the adoption of email and word processing [22,23]. These issues raise question as to suitability of TAM or UTAUT for the assessment of user experiences and, the perceptions of those who continue to use, or have used, the technology being investigated [24–27] in healthcare, as intended in this study.

The TAM model, first introduced by Davis in 1985 [18], has been extensively adapted and used in the developing world for assessing the potential adoption of technology by patients [28–30]. UTAUT [19], and subsequent variants of both TAM and UTAUT, were spawned from TAM. They collectively assume that users will use a technology primarily based on their perception of its usefulness and ease of use. However, other factors have been introduced in variations of the models. Indeed, when reviewing the application of UTAUT2, perhaps the most comprehensive model, it was noted most studies combined this model with external theories, and it could not be used ‘standalone’ [31]. Furthermore, the literature shows the variance in adoption factors for which these models account ranges from 30 to 40% [32]. Thus, there are other determinants that affect the acceptance of a technology in healthcare that TAM and UTAUT currently do not address [33].

Building on TAM and UTAUT, it has been proposed that for successful adoption of new technology in healthcare, the determinants should go beyond the perception of the technology’s usefulness and ease of use to encompass many other elements [34,35]. Proposed elements include: user involvement in the design process, resource allocation of an organisation’s decision-making process, user availability and willingness to use technology, and socio-cultural and political considerations. A more detailed consideration of the factors that impact (enable or impede) technology adoption by patients is required to more successfully predict its use. Failure to identify or analyse these factors, or lack of consideration of relevant factors, may be responsible for failure to use the technology [36,37].

TAM, and thereby UTAUT, are both based on the theory of reasoned action which suggests that social behaviour is motivated by an individual’s attitude. They are used to predict information system use [38], i.e. an individual is more likely to behave in a certain way when they believe that people important to them want them to behave that way [39]. In technology acceptance research, social influence is always measured under the subjective norm and its effect on the adoption and use of technology by individuals [40]. However, two issues arise. First, the subjective norm alone may not address the complex and broader social determinants that affect the health-related behavioural choices of people. Second, is the subjective norm an appropriate assumption? Patients, and sometimes healthcare workers, may not have any ‘choice’ when a health system or health facility unilaterally introduces an eHealth or mHealth intervention. Consequently, a prerequisite for the successful adoption of a new technology in healthcare depends on properly understanding the full spectrum of factors that may impact adoption among potential users in prevailing circumstances [20,41]. In light of these limitations, Shachak and colleagues recommend future research on health information technology implementation and use should shift from the existing theories of TAM of UTAUT to a multi-faceted approach to address the complexity of factors affecting technology implementation and use in healthcare [20].

This study addressed these issues by applying findings from published empirical research of real-world implementations to understand the spectrum of factors that impact adoption of mHealth interventions by patients in the developing world [17]. That research had identified and described seven categories of factors based on a structured literature review of 54 articles that identified factors impacting mHealth adoption by patients in the developing world. The seven categories were: Cost and ownership, user characteristics, language and literacy, infrastructure, collaboration and funding, governance, and system utility. These had been identified as factors that needed to be considered when examining the adoption of mHealth in the developing world. Furthermore, given the steady growth in the presence and use of mobile devices for communication, entertainment, and banking in the developing world, it can be anticipated there will be greater exposure to and familiarity with apps in general. This makes the views of those with prior mHealth experience regarding factors impacting mHealth adoption more relevant than those of naïve users.

The study also leveraged the Mobile Technology for Community Health (MoTeCH) system deployed in the Ewutu Senya East and West districts of the Central region of Ghana [42], by enrolling women with experience using the app for the study. MoTeCH was made up of two interconnected mobile applications, Mobile Midwife, and the Client Data Application. The Mobile Midwife app enabled pregnant and post-natal women to receive SMS or pre-recorded audio messages on maternal and child welfare matters in their local dialects on either their own mobile phones, that of an immediate relative, or of a volunteer in the community. The information sent was based on gestational age or the age of the child. The Client Data Application was used by community health workers in identifying and processing care for mothers and children in their catchment areas who are either due or overdue depending on either the gestational age or the age of the child [42].

Given the absence of any published ‘patient-specific’ framework, and given the prevailing use of TAM and UTAUT dependent findings and their identified limitations (e.g., limited accounting of total variance; lack of consideration of the subjective norm), an alternative approach to identifying relevant adoption factors is desirable. The objectives of this study were twofold. First, to describe the development of a new instrument, the Patient mHealth Technology Adoption Questionnaire (PmTAQ), for assessing the intention of patients in the developing world to adopt mHealth systems and to test its validity and reliability. Second, to evaluate the utility of PmTAQ in the development of a new model - the mHealth Adoption Impact Model (mAIM). To achieve this, a novel approach was taken (using empirical real-world research and the views of patients who had previously used an mHealth intervention) to identify factors these users believed would influence others to use and accept mHealth.

Such an instrument could be used in research and education and also to facilitate future implementations of mHealth for patients in the developing world.

2. Methods

The methods used to develop the new PmTAQ and to test its reliability and validity are first described. As the instrument was found to be valid and reliable, the methods used for the development of the measurement model, the mHealth Adoption Impact Model (mAIM), are then described. The detailed results for the instrument development are presented in the Results section.

2.1. Patient mHealth Technology Adoption Questionnaire (PmTAQ) development

A draft instrument with eight constructs was developed following the design of other currently available instruments [43–45]. The constructs were based on a 7-element conceptual model [17] with an additional construct, the intention to adopt, added to show the relationship between the conceptual constructs and their impact on an individual's intention to adopt mHealth. Its face validity was assessed by five lay persons, and content validity by three experts in the field. The instrument was then modified based upon feedback and pretested by 15 mothers who had previously used mHealth for maternal care. The findings were used to refine the instrument.

2.2. Instrument content

The PmTAQ was made of 39 items addressing eight constructs (Table 1). Items were scored using a 7-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree) (Appendix 1).

2.3. Sample

The study population was mothers who had participated in MoTeCH in the Ewutu Senya Municipal District of the Central Region of Ghana. Seventeen health posts within the district were divided into nine clusters. Communities within each cluster were sensitised to the research beforehand with the assistance of community health nurses. The inclusion criteria were: mothers attending a scheduled child welfare clinic, registered MoTeCH users, and had used MoTeCH for at least six-months. These mothers were invited to participate in return for a small cash incentive, and informed consent obtained. Mothers receiving any other services at the health post, or who were not registered as MoTeCH users, were excluded.

Literature recommendations regarding the appropriate sample size to use when conducting a factor analysis vary considerably [46]. Here the sample size was estimated based on the components-to-factors ratio [47], and using a ratio of 15 cases per parameter, the sample size was determined to be 585. Systematic sampling (every second mother) was used to enrol a random sample of 612 mothers, with equal distribution from the nine clusters. Systematic sampling was chosen because it is simpler and more straightforward than other probabilistic sampling methods [48]. A 10% dropout rate was presumed.

2.4. Data analysis

Principal component analysis with varimax rotation was used to generate the component transformation matrix to verify sampling adequacy for factor analysis [49]. The reliability of the instrument was assessed using Cronbach's α measure for internal consistency among items in the instrument [50]. IBM SPSS version 20.0 was used for data analysis, and alpha was set at 5%.

2.5. Development of a measurement model

As the instrument was found to be valid and reliable, confirmatory factor analysis (CFA) was used to confirm and trim constructs and items in the PmTAQ and specify which question item load on which construct and which constructs are correlated. To achieve this, the constructs of the instrument were categorised into two groups, exogenous and endogenous. The exogenous constructs were: collaboration and funding (CF), availability of enabling infrastructure (AN), language, literacy, and training (LLT), and governance (GOV). The endogenous constructs were: ownership and cost (OC), user characteristics (UC), system utility (SU) (divided into SUS - first three items, and SUH - the last three items under the SU variable), and intention to adopt (IA). SUS relates to questions addressing: SU1 - perception of satisfaction; SU2 - services received not different from standard care; SU3 - actual satisfaction after service. The other questions under the SU category were grouped as SUH, relating to questions: SU4 - increases knowledge about health status, SU5 - system generating reliable information, and SU6 - standard care health outcomes not better than mHealth. The constructs and items were then modelled based on hypothesised causal relationships between latent factors and their observed indicator constructs. The confirmatory factor analysis was then performed to assess the fit between the observed data based on the hypothesised causal relationship. The model was considered to be a good fit (Appendix 2 and 3), and structural equation modelling was undertaken to find the existence of the relationships between the constructs and items. The structural model was analysed using multiple reflector indicators, and their values were calculated.

2.6. Ethical approval

Ethical approval was provided by the Biomedical Research Ethics Committee (BREC) of the University of KwaZulu Natal, South Africa (BE499/15), and by the Ghana Health Service, Ethical Review Committee (GHS-ERC January 06, 2017). All participants provided written informed consent.

3. Results

3.1. Patient mHealth Technology Adoption Questionnaire (PmTAQ) development

The returned surveys were filtered. One case was incomplete and excluded, and 26 were eliminated during normality testing, leaving 585 for analysis. A Kaiser–Meyer–Olkin (KMO) [51] measure of 0.844 verified the sample size adequacy for factor analysis. Bartlett's test of sphericity (χ^2 (741) = 15901.339, $p < 0.05$) further indicated that correlations between items were sufficiently large for principal component analysis [52]. Eigenvalues were calculated for each principal component in the data and summarised in the scree plot (Fig. 1), which shows eigenvalues with the corresponding components on the factorial axes. Eigenvalues for the first eight components were greater than one and explained 68.8% of the variance (Appendix 1).

Reliability analysis was conducted, and internal consistency was high, with a mean Cronbach's alpha of 0.82 (range 0.81–0.83). Summary statistics for the data are shown in Appendix 1. The mean and standard deviations showed limited dispersal from central tendency. There was general agreement or strong agreement with all statements, with no median Likert score less than six. Questions with the least variation in range of Likert scale responses were those related to collaboration and funding, governance, system utility, and intention to adopt. The item with the lowest standard deviation was IA3 ("My intention to adopt mHealth will be as a result of the availability of appropriate literacy and training") with a value of 0.43 and a mean of 6.8. The item with highest standard deviation was LLT3 ("Ability to operate the mHealth device by oneself will promote adoption"), with a value of 1.2 and a mean of 5.1. The overall mean and standard deviation for the 39 scale items was found to be 241.8 and 10.84, respectively. The mean values for the PmTAQ ranged from 235.06 to 235.36, representing a decrease in value ranging from 5.6 to 6.8 for the items listed. The Pearson coefficient of correlation ranged from 3% to 57.4%. All the items showed relatively moderate correlation coefficients and showed relevance on the scale.

3.2. Development of the measurement model

A Confirmatory Factor Analysis (CFA) then conducted to test whether the data fit a hypothesised measurement model [53]. Results from the Confirmatory Factor Analysis (CFA) shows that convergent, discriminant and nomological validity were established for the measurement model to be (Appendices 2 and 3).

The components on the instruments were categorised into two groups, exogenous and endogenous. The exogenous components were: collaboration and funding (CF); availability of enabling infrastructure (AN); language, literacy, and training (LLT); and Governance (GOV). The endogenous components were: ownership and cost (OC); user characteristics (UC); System Utility (SU) (divided into SUS -first three items, and SUH - the last three items under the SU variable); and intention to adopt (IA). The measurement model was run using SPSS AMOS 23. Based on model fit indices the measurement model can be considered a good fit (Table 2).

Based on the estimates from the measurement model, structural equation modelling was undertaken to find the existence of the relationships between the components and items and analysed using multiple reflector indicators. Their values were calculated (Table 3).

The structural model (Fig. 2) was analysed using multiple reflector indicators, and their values are shown in Table 3 below.

All of the indices for the model are within acceptable limits and almost all the covariances are within the + 2.00 and − 2.00 assumption rule. These findings demonstrate the model is fit for examining the causal effect between the constructs and can be applied to a much larger sample or the general population.

3.3. Findings from the model

Structural modelling showed direct and mediating effects. The direct effects were that collaboration and funding (CF) have a positive effect on ownership and cost (OC). Availability of enabling infrastructure (AN) has a positive effect on ownership and cost (OC). System utility in relation to service satisfaction (SUS) as a positive effect on intention to adopt (IA). Finally, SUS has a positive effect on User characteristics (UC). The mediating effects were: ownership and cost (OC) is a mediator between collaboration and funding (CF) and SUS. SUS is a mediator between OC and IA. OC is a mediator between AN and SUS. SUH is a mediator between language, literacy and training (LLT) and UC. UC is a mediator between SUS and intention to adopt (IA). Finally, UC is a mediator between SUH and intention to adopt (IA). The resulting model is termed the mHealth Adoption Impact Model (mAIM).

4. Discussion

The PmTAQ and the resulting mAIM were developed in response to the need to improve adoption and use of mHealth by patients in the developing world. The new model is based on eight components derived from a review of the empirical literature on factors influencing patients' adoption of mHealth in the developing world. In addition, the thirty- nine items used in the PmTAQ were developed based on validated frameworks. Further, after face and content validation, the PmTAQ was used by a large sample of patients who had used an mHealth solution (MoTeCH) and was shown to be valid and reliable, leading to the formulation of the mAIM. mAIM accounts for 68.8% of the variance in factors impacting adoption, comparable to or better than recent and evolved TAM- or UTAUT-based models of patient or population studies which varied from 30 to 40% [32].

PmTAQ and mAIM appear to be the first time an instrument and its resulting model have been developed based on data collected from actual mHealth system users in the developing world. These are essential developments in the health sector, especially for patients, because they do not necessarily have a choice regarding the technology interventions that are implemented for their use. TAM, UTAUT and their variants are based on the theory of reasoned action, people's intentions to change behaviour, their perceptions of the benefit of using the technology, and how easy it will be to use the technology, among other precepts. The theory of reasoned action and behavioural change does not address all of the major factors influencing the adoption of mHealth by patients [60, 61].

In healthcare, the circumstances around patient adoption of, for example, mHealth are different to people deciding to use a new technology such as a smartwatch, new software, or an electric motor car. These are choices that an individual makes, which inevitably influences adoption behaviour. In contrast, many eHealth interventions are implemented by governments (particularly in the developing world), institutions, insurers and even clinicians. The patients face a *fait accompli* – they have no option: their information is entered into an electronic medical record; or their doctor arranges a videoconferenced consultation with a specialist; or the government implements a maternal health programme (e.g. MoTeCH); or their doctor 'advises/tells' them to enter their daily food intake into an app or to complete a weekly mood assessment using an app. This is particularly relevant in the more paternalistic societies and health systems prevalent in the developing world.

The ‘standard’ tools used for predicting the adoption of new health-related technologies are based on models such as TAM, UTAUT, etc. These may well be valid when patients decide for themselves whether they will, for example, download and use a behaviour change fitness or diet app on their phone, but their validity in other settings have been questioned [38]. Another approach based on empirical evidence is needed.

The PmTAQ and mAIM are based on empirical evidence. PmTAQ initially used empirically determined constructs identified as the key issues that must be addressed [17]. Similarly, other validated instruments were reviewed, and lessons learnt were applied to the PmTAQ design. In addition, the PmTAQ underwent face and content validation, and pre-testing to improve the final instrument. The instrument was pilot tested using a large population of mHealth experienced mothers, allowing confirmatory factor analysis to develop the measurement model (as suggested by Hair et al. (2009) [62] and Kline (2011) [63], leading to the use of structural equation modelling to develop mAIM. All indices for the model were within acceptable limits.

Finally, this study is not based on behaviour theory, but approaches the problem from a real-world perspective. As such it presents a novel and alternate approach to developing a framework to address adoption of mHealth. It provides a practical framework as argued by Shachak et al. [20] to address the complexity of issues affecting patients’ mHealth adoption and this now needs to be applied in the field.

A strength of the study is its focus on patients. Given that the primary beneficiaries of mHealth are patients and healthcare providers, similar research exploring factors impacting adoption of mHealth by healthcare workers would be valuable.

5. Limitations

The instrument that led to the model was developed based on resources focusing only on the developing world that were retrieved from two electronic literature databases. Also, the inclusion criteria were limited to English language resources only. These factors may have introduced a limitation to the original research, and thereby this research, by reducing the number of resources reviewed and lowering the likelihood of identifying other relevant factors from other databases and published in languages other than English. Consequently, the instrument and structural model may not comprise all possible factors that influence patient mHealth adoption.

6. Conclusions

This study has confirmed the reliability and validity of the PmTAQ instrument, which uses 39 items within eight constructs to assess factors that impact the adoption of mHealth by patients in developing countries. Principal component analysis confirmed the importance of system utility, literacy and training, governance, user characteristics, cost and ownership, availability of infrastructure, collaboration and funding, and intention to adopt. The model fit indices from the structural model confirmed the acceptability of the model."

Successful adoption of mHealth by patients in the developing world depends on an understanding of the full spectrum of factors that may impact adoption, which extend beyond perception of an mHealth application's usefulness and ease of use. The PmTAQ addresses these additional factors and is a suitable instrument for researchers, implementers, and policy-makers to better understand patient adoption of mHealth in the developing world.

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APPENDICES

APPENDIX 1

EXPLORATORY FACTOR ANALYSIS

	Component										
	1	2	3	4	5	6	7	8	mean	Std. Dev	Median
SU1: The perception that mHealth provides satisfactory services will promote use.	.857								6.66	0.473	7
SU2: If mHealth services are not different from standard care it will promote use	.848								6.62	0.490	7
SU3: If the experience after using mHealth is satisfactory it will promote use	.834								6.48	0.500	6
SU4: If mHealth helps me get more knowledge about my health status it will promote use.	.779								6.55	0.498	7
SU5: If the information received through mHealth is reliable it will promote use.	.773								6.59	0.492	7
SU6: If the health outcomes in using standard care is not better than in mHealth it will promote use	.721								6.60	0.490	7
LLT1: Receiving mHealth services in a language I understand will promote use		.918							6.12	0.946	6

	Component										
	1	2	3	4	5	6	7	8	mean	Std. Dev	Median
LLT2: Communicating with my healthcare provider in a language I understand will promote use.		.907							5.93	1.164	6
LLT3: Ability to operate the mHealth device by oneself will promote adoption.		.862							5.07	1.188	6
LLT4: Ability to read and write will promote use.		.750							5.86	1.062	6
LLT5: Provision of appropriate training on device use to access services will promote use.		.715							5.91	0.842	6
LLT6: Ability to communicate in my local language to access mHealth services will promote use		.575							5.57	1.087	6
GOV1: Securing my data from unauthorized access will promote use.			.922						6.36	0.740	6
GOV2: If healthcare workers carry out their services professionally like they will do in standard care it will promote use.			.911						6.50	0.517	7
GOV3: If my data will not be divulged to third parties without my consent it will promote use			.898						6.33	0.591	6
GOV4: If there are regulation and standards governing the service provision it will promote use.			.848						6.34	0.588	6
GOV5: If the integrity of the system can be guaranteed (i.e. The one communicating with me is the accredited healthcare provider) it will promote adoption.			.440						6.36	0.584	6
UC1: The perception that mHealth systems are easy to operate will promote				.927					6.46	0.956	7
UC2: Designing mHealth to reflect the local context of				.891					6.39	0.671	6

	Component										
	1	2	3	4	5	6	7	8	mean	Std. Dev	Median
standard care will promote use.											
UC3: The readily availability of health workers to provide service will promote use.				.764					5.96	0.852	6
UC4: Gender can affect phone ownership for mHealth use.				.708					6.22	0.742	6
UC5: Age can affect one's use of mHealth.				.686					6.27	0.715	6
UC6: Socio-cultural issues (beliefs) can affect one's use of mHelth.				.593					6.46	0.674	7
OC1: Availability of mHealth devices and accessories will promote use.					.947				5.75	0.877	6
OC2: The affordability of mHealth devices and accessories will promote use.					.901				6.05	0.759	6
OC3: The affordability of mHealth services will promote use.					.833				6.11	0.655	6
OC4: Ownership of mobile devices by patients to access service anytime and anywhere will promotes use.					.793				6.22	0.645	6
OC5: Sharing of mHealth device for accessing services will affect use.					.541				6.16	0.662	6
AN1: Availability of Reliable telecommunication network services will promote use.						.903			5.72	1.077	6
AN2: Availability of mHealth devices and accessories will promote use						.886			5.66	0.776	6
AN3: Availability of adequate human resource (nurses, doctors, IT support staff, etc.) will promote (use doctors, IT support staff, etc.) to provide the service.						.882			5.79	1.054	6
AN4: The readily availability of electric power to sustain the						.713			5.74	0.921	6

	Component										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**mean**	**Std. Dev**	**Median**
service will promote use.											
IA1: My intention to adopt mHealth will be as a result of the availability of mHealth devices and subsidy.							.903		6.40	0.490	6
IA2: My intention to adopt mHealth will be as result of the availability of reliable network and supporting government policy.							.813		6.59	0.491	7
IA3: My intention to adopt mHealth will be as a result of the availability of appropriate literacy and training.							.788		6.76	0.427	7
CF1: Perception of collaboration among relevant agencies (e.g., Ghana health Service, Ministry of Health, Telcos, etc.) will promote use								.692	5.75	0.740	6
CF2: Promotion and advocacy of mHealth use by the government and NGOs (for example: funding and promoting mHealth sensitization through radio, television, bill boards and other forms of ads) will promote use.								.689	6.17	0.926	7
CF3: Subsidized prices for mHealth handsets and related accessories will promote use.								.606	6.17	0.746	6
CF4: Community ownership of mHealth programs promote adoption.								.597	5.99	0.949	6
Eigenvalues	7.156	4.68	3.57	3.27	2.71	2.20	2.02	1.17			
Variance Explained (%)	18.34	12.01	9.15	8.39	6.94	5.64	5.31	3.012			
Cronbach a(%)	91.3	88.4	89.9	84.8	85.6	88.7	79.4	77.3			
Total Variance Explained (%)	68.82										
Total Reliability of instrument (%)	82.4										
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.844										

	Component										
	1	2	3	4	5	6	7	8	mean	Std. Dev	Median
Bartlett's Test of Sphericity		Approx. Chi-Square									15901.339
		df									741
		Sig.									.000
Chi-Square goodness of fit		Value									585.000
		D									584
		Sig.									0.481

APPENDIX 2

CONVERGENT VALIDITY

Convergent validity	CF	OC	SUS	IA	AN	LLT	GOV	SUH	UC
CR	0.878	0.895	0.850	0.893	0.897	0.941	0.883	0.865	0.949
Factor loadings = √CR	0.937	0.946	0.922	0.945	0.947	0.970	0.940	0.930	0.974
Error Variance = 1-√CR	0.063	0.054	0.078	0.055	0.053	0.030	0.060	0.070	0.026

APPENDIX 3

DISCRIMINANT VALIDITY

			Correlation Estimate (r)	r square	AVE1 & AVE2 AVEs greater than r2	Discriminant Validity
CF	<–>	AN	.254	0.065	0.648 0.688	Established
CF	<–>	LLT	.152	0.023	0.648 0.801	Established
AN	<–>	LLT	.379	0.144	0.688 0.801	Established
AN	<–>	GOV	.112	0.013	0.688 0.676	Established
LLT	<–>	GOV	.091	0.008	0.801 0.676	Established
CF	<–>	GOV	−.014	0.000	0.648 0.676	Established
SUS	<–>	IA	.572	0.327	0.657 0.738	Established
OC	<–>	SUS	.167	0.028	0.684 0.657	Established
CF	<–>	SUS	.033	0.001	0.648 0.657	Established
AN	<–>	SUS	.232	0.054	0.688 0.657	Established
LLT	<–>	SUS	.084	0.007	0.801 0.657	Established
IA	<–>	SUH	.147	0.022	0.738 0.682	Established
SUS	<–>	SUH	.093	0.009	0.657 0.682	Established
SUS	<–>	UC	.308	0.095	0.657 0.681	Established
IA	<–>	UC	.571	0.326	0.738 0.681	Established
LLT	<–>	IA	.169	0.029	0.801 0.738	Established
OC	<–>	IA	.335	0.112	0.684 0.738	Established

			Correlation Estimate (r)	r square	AVE1 & AVE2 AVEs greater than r2	Discriminant Validity
AN	<–>	IA	.450	0.203	0.688 0.738	Established
CF	<–>	IA	.130	0.017	0.648 0.738	Established
GOV	<–>	IA	.089	0.008	0.676 0.738	Established
CF	<–>	OC	.388	0.151	0.648 0.684	Established
AN	<–>	OC	.626	0.392	0.688 0.684	Established
LLT	<–>	OC	.400	0.160	0.801 0.684	Established
OC	<–>	SUH	.116	0.013	0.684 0.682	Established
GOV	<–>	OC	.079	0.006	0.676 0.684	Established
OC	<–>	UC	.204	0.042	0.684 0.681	Established
GOV	<–>	UC	.062	0.004	0.676 0.681	Established
SUH	<–>	UC	.136	0.018	0.682 0.681	Established
LLT	<–>	UC	.041	0.002	0.801 0.681	Established
AN	<–>	UC	.230	0.053	0.688 0.681	Established
CF	<–>	UC	.113	0.013	0.648 0.681	Established
AN	<–>	SUH	.241	0.058	0.688 0.682	Established
CF	<–>	SUH	.111	0.012	0.648 0.682	Established
GOV	<–>	SUH	.323	0.104	0.676 0.682	Established
LLT	<–>	SUH	.154	0.024	0.801 0.682	Established
GOV	<–>	SUS	.116	0.013	0.676 0.657	Established

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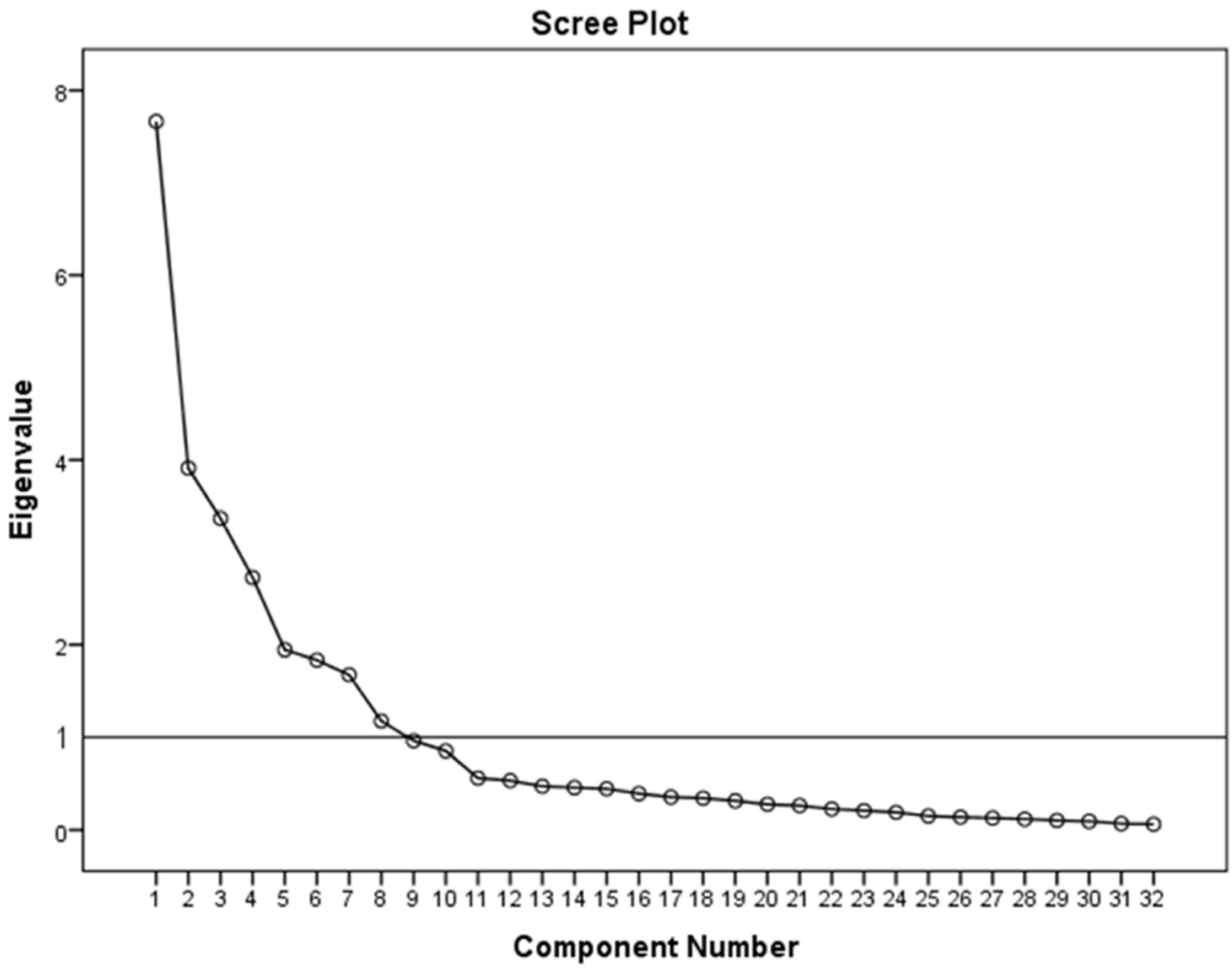

Fig. 1.

Scree plot of eigenvalues (y acceptable =>1) and component numbers (x-axis).

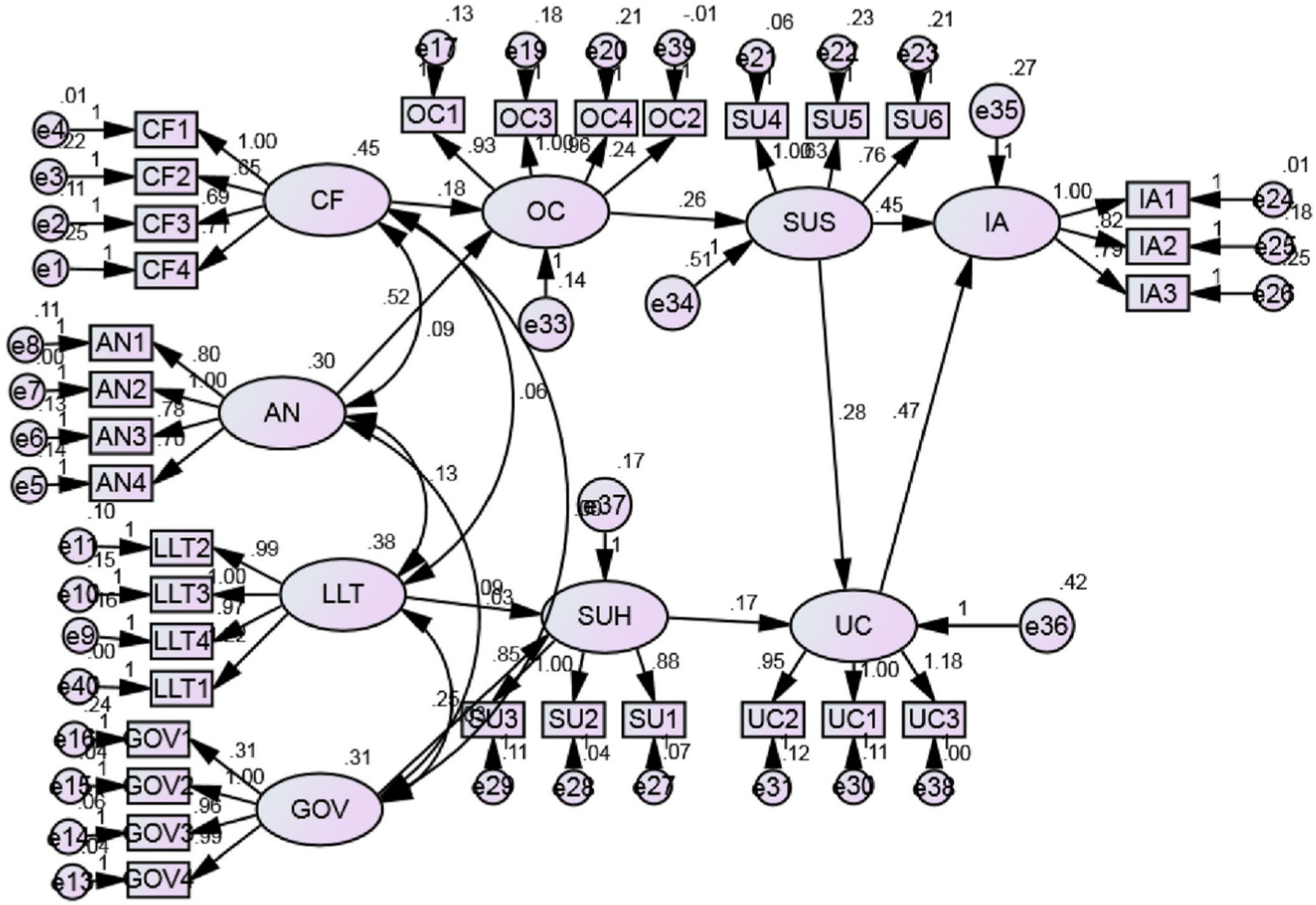

Fig. 2.

mHealth Adoption Impact Model (mAIM) ("e's" are the error terms of the latent and observed components).

Table 1

Components and the issues that they address.

Construct	Addresses	Items
1. User characteristics	Attitude based on social cultural orientation and local context issues	UC1-UC6
2. System Utility	Adoption based on systems usability and effectiveness	SU1-SU6
3. Language, literacy, and training	The influence of the language used for communication, user literacy, and any training	LLT1-LLT6
4. Availability of enabling infrastructure	Devices and the network system availability	AN1-AN4
5. Governance	The influence of the presence or absence of security, confidentiality, privacy, and standards	GOV1-GOV5
6. Collaboration and funding	The influence of the presence or absence of multi-sectorial engagement and funding or subsidies	F1-CF4
7. Ownership and cost	The influence of the cost of devices, services, and ownership	OC1-OC5
8. Intention to adopt	The attitude of patients towards use and their intention to use mHealth in future	IA1-IA3

Table 2

Model fit indices for the measurement model.

Test	Result	Acceptance criterion
Chi-square to the degrees of freedom CMIN/DF	1.313	>2 or 3 [54,55]
Goodness of fit index	0.945	>0.90 [56]
Adjusted goodness of fit index	0.931	>0.90 [56]
Normed fit index	0.963	>0.90 [56]
Incremental fit index	0.991	>0.90 [57]
Tucker Lewis index	0.989	>0.95 [57]
Comparative fit index	0.991	>0.93 [56]
Root mean square error average	0.023	<0.06 [55]

Table 3

Results of the structural equation modelling and the acceptance criteria.

Test	Result	Acceptance criterion
Chi-square to the degrees of freedom CMIN/DF	1.805	<2 or 3 [54,58]
Root mean square residual	0.032	<0.08 [57,59]
Goodness of fit index	0.922	>0.90 [56]
Normed fit index	0.946	>0.90 [56]
Comparative fit index	0.975	>0.93 [56]
Incremental fit index	0.975	>0.90 [56]
Tucker Lewis index	0.973	>0.95 [57]
Root mean square error average	0.037	<0.06 [55]