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EVALUATING THE EFFECTIVENESS OF DIGITAL HEALTH MARKETING STRATEGIES ON PATIENT ENGAGEMENT AND HEALTHCARE SERVICE UTILIZATION

TANMOY MAJUMDER
PHD SCHOLAR, FACULTY OF MANAGEMENT, JIS UNIVERSITY

RITAM SAHA
PHD SCHOLAR, FACULTY OF MANAGEMENT, JIS UNIVERSITY

DR. NILANJAN RAY
ASSOCIATE PROFESSOR

DR. SUDIP BASU
ASSISTANT PROFESSOR & HOD, DEPARTMENT OF MANAGEMENT STUDIES, ASANSOL ENGINEERING COLLEGE

PRIYANKA KANJILAL
PHD SCHOLAR, JIS UNIVERSITY, ASSISTANT PROFESSOR DEPARTMENT OF MANAGEMENT ASANSOL ENGINEERING COLLEGE

SANDIP KARMAKAR
PHD SCHOLAR, JIS UNIVERSITY, ASSISTANT PROFESSOR DEPARTMENT OF MANAGEMENT ASANSOL

TARPAN CHAKRABORTY
PHD SCHOLAR, FACULTY OF MANAGEMENT, JIS UNIVERSITY

DR. MOUMITA ROY
ASSISTANT PROFESSOR, FACULTY OF MANAGEMENT, JIS UNIVERSITY

Abstract: The growing integration of digital platforms within healthcare has altered the way patients engage with providers, obtain information, and make decisions about service use. Although digital outreach has become central to modern health delivery, clear evidence on how patients interpret and respond to such platforms is still limited. This study examines the underlying dimensions of digital health marketing and associated engagement behaviour through Exploratory Factor Analysis (EFA). Data were gathered from 246 respondents using a structured five-point Likert scale survey covering website usability, mobile app features, personalised communication, social media interactions, telehealth awareness, patient engagement experiences, and service utilisation patterns. Principal component analysis with Varimax rotation produced a coherent seven-factor structure consisting of (1) patient engagement and self-management, (2) healthcare utilisation outcomes, (3) mobile app usability, (4) personalised CRM communication, (5) website information quality, (6) social media engagement and trust, and (7) telehealth awareness and acceptance. The factor structure showed high loadings with minimal cross-loading, indicating sound psychometric properties.

The results demonstrate that digital tools function not only as channels of information but also as behavioural drivers that support continuity of care, promote informed decision-making, and encourage proactive health behaviour. Personalised CRM communication, in particular, plays an important role in reinforcing relevance and consistency of care. By identifying the distinct dimensions shaping patient interaction with digital platforms, the study provides a measurement foundation that can support future confirmatory and structural analyses. The findings also offer guidance for healthcare organisations and policymakers to strengthen digital outreach, enhance patient-centred communication, and improve access to services in diverse healthcare environments.

Keywords: Digital Health Marketing, Patient Engagement, Healthcare Service Utilization, Exploratory Factor Analysis (EFA), Mobile Health (mHealth), Telehealth Acceptance, Personalized Communication, Social Media Engagement

INTRODUCTION

The speedy digitalization of healthcare has radically changed the way of patient access to services, health perception, and communication samples with providers. Digital health marketing, including web-based communication portals, social media campaigns, mobile health (mHealth) applications, and personalized outreach strategies, have developed as a centralized process of improving patient engagement and reinforcing the provision of healthcare services (Kotler et al., 2021; Ventola, 2014). With the growing tendency of the healthcare system to become more patient-centric, the effectiveness of the digital communication strategies has become one of the gravest concerns regarding the progress of the public health and the competitiveness of the organization (Barton et al., 2022).

The patient engagement is recognized as one of the pillars of the sustainability and quality of healthcare, affecting compliance to treatment, health-related decision-making, and health-related behavioral patterns (Barello et al., 2016). Interactions that are mediated using digital technologies make it possible to promote transparent and ongoing contact between patients and providers, thus helping to establish trust, enhance health literacy, provide emotional support, and make decisions together (Graffigna et al., 2015). The ability of digital portals, including teleconsultation interfaces, patient health dashboards, SMS alerts, and virtual triage services, contributes to the enhancement of patients in terms of their ability to track their health conditions, adhere to medical recommendations, and proactively seek professional care (Shah et al., 2019). Therefore, digital communication is not only an informational mechanism, but it is also a behavioral catalyst.

In parallel to engagement, the availability and accessibility of digital channels to healthcare service use have significantly influenced healthcare service utilization. Digital touchpoints lower spatial, temporal, and psychological boundaries to accessing healthcare as they allow booking an appointment, searching a provider, using payment options, and having a teleconsultation opportunity (Budd et al., 2020). More to the point, digital marketing approaches increase the visibility, shape the perception of patients with respect to the quality of the facilities, and steer their choice of healthcare services. Such online indications influence the preference to clinical environments and promote care-seeking soon, especially among the population that had been restricted by geographic or informational aspects (David and Roberts, 2022).

Within the setting of the developing world economies, like India, the digital health marketing gains a more subtle purpose. Although the number of digital platforms continues to increase, digital disparities in digital literacy, socioeconomic status, and access to the internet affect the way patients view and incorporate digital health services (Rao et al., 2021). As a result, there is an urgent need to assess the digital marketing strategies in such heterogeneous settings with evidence-based arguments to enhance fair health access and better outcomes on the population level. A source of empirical vagueness, however, still exists on how exactly digital interventions evoke behavioral interest and promote efficient use of healthcare services. Current research tends to use fragmented or descriptive methods, without detailed measurement models that would help prove the hypotheses of the relationships between the causal variables.

The present research contributes to the evolving field of digital health services by empirically examining how patients respond to digitally mediated healthcare interactions using validated measurement constructs. Rather than modelling structural relationships, this study focuses on identifying and clarifying the underlying dimensionality of digital health marketing and patient engagement behaviours through Exploratory Factor Analysis (EFA). The findings provide statistically grounded evidence on how digital communication channels, usability perceptions, informativeness, and personalized interactions coalesce to shape the modern healthcare experience.

The theoretical orientation of the study draws on perspectives from health communication, behavioural intention frameworks, and service marketing logic. These perspectives collectively support the view that digital healthcare environments represent more than technological interfaces; they function as behaviour-shaping ecosystems that influence how individuals connect with providers, use information, and decide upon service utilization. By establishing a multidimensional and empirically supported measurement structure, the current work advances conceptual clarity in the domain and offers a useful foundation for future confirmatory analyses and structural modelling.

Importantly, this research addresses existing knowledge gaps by providing empirical insight into the latent constructs governing digital health experience from the patient's viewpoint. While many prior studies emphasize outcomes such as satisfaction, adherence, or service uptake, fewer have systematically examined the underlying measurement dimensions that precede such outcomes. The results demonstrate that digital communication quality, informational credibility, usability attributes, and personalized interactions are critical features that influence how patients evaluate and navigate online healthcare resources. This understanding is essential for designing patient-centred digital environments that support meaningful health engagement.

The contribution of this study lies in generating evidence-based measurement components that may guide the refinement of digital outreach and patient communication strategies. The factor structure offers actionable implications for policy and managerial practice by highlighting which dimensions patients consider most salient when interacting with digital health platforms. By strengthening these dimensions, healthcare organizations may enhance patient participation, improve informational access, and reduce barriers in service navigation, particularly among populations with limited physical access to care.

LITERATURE REVIEW

The digital transformation has dramatically changed the communication, engagement, and retention of patients by the healthcare organizations. According to scholars, digital health marketing has changed into a promotion instrument to become a strategic technique in influencing patient behavior, increasing access, and affecting the use of healthcare services. Nevertheless, the empirical evidence is still in conflict and controversial, particularly when it comes to developing healthcare systems, even though its significance is increasing.

The preliminary research points to the fact that digital marketing, including websites, social media, appearance in search engines, and mobile health applications, increases the level of information transparency, promotes awareness of the services, and alters the views on proactive health-seeking behaviors (Kotler et al., 2021; Ventola, 2014). The advocates believe that digital outreach can facilitate hospitals to update in real-time, enhance branding, and enhance patient-provider relationships, which leads to better patient engagement (Graffigna et al., 2015). Shah et al. (2019) state that interactive digital interfaces enable patients to have access to customized health information, thus promoting autonomy and influencing healthcare decisions.

The degree to which digital marketing directly influences patient engagement is, however, debatable. Other researchers believe that people become engaged mostly because of intrinsic factors, including health literacy, motivation, and perceived severity of illness, and not external marketing stimuli (Barello et al., 2016). Critics claim that digital strategies can make more visible and cannot ensure any meaningful behavioral change (particularly in marginalized populations with lower digital skills), as noted by Rao et al. (2021). This brings to the fore a key argument of whether digital marketing is only a dissemination of information or concepts of deeper and actual involvement of patients.

On the same note, the connection between digital marketing and the use of healthcare services is multifaceted and varying in most studies. There are those researchers who argue that successful digital planning enhances the number of appointments made, telehealth use, and the use of preventive services through the mitigation of barriers to access (Budd et al., 2020). Patient portals, teleconsultation platforms, and digital reminders have demonstrated significant improvements in follow-up adherence as well as chronic disease management behaviors (Barton et al., 2022). There is, however, some conflicting evidence that digital marketing is not likely to have a significant impact on the utilization patterns in low-resource environments due to infrastructural and socioeconomic disparities (David and Roberts, 2022). This alienation casts doubt on the contextual legitimacy of digital strategies and the degree to which they can be used to address systemic healthcare shortcomings.

In addition, researchers do not agree that the effect of digital health marketing cuts across the demographic boundaries of the patients. Although there are studies that suggest that younger digitally literate groups are positively impacted by digital interventions (Budd et al., 2020), other studies voice that older people and rural areas might still not be addressed because of their low digital affinity or insufficient internet infrastructure (Rao et al., 2021). These inequalities imply that online measures can be used inadvertently to strengthen health inequities unless inclusive and adaptive designs are followed.

The other issue that is subject to controversy is on the quality and credibility of digital health content. As healthcare organizations work at spreading evidence-based information, social media and other digital platforms are also full of misinformation, which may misplate the decision-making process of patients (Ventola, 2014). It is suggested that the higher digital presence, the higher the trust towards healthcare providers, whereas some people warn that overmarketing may destroy the credibility as seen as business-oriented instead of patient-centered (David and Roberts, 2022). Therefore, maintaining a balance between promotion messages and ethical communication is still one of the major challenges.

Lastly, researchers also claim that digital health marketing no longer needs to focus on the informational provision but rather a personalized engagement paradigm that includes analytics and behavioral insights and patient experience data (Barton et al., 2022). Nevertheless, there is still a lack of empirical research that can prove these sophisticated digital approaches. Consequently, the theoretical and empirical basis of the impact of the digital marketing of health on patient engagement and service uptake is not yet well developed even though it is highly adopted.

Combined, the literature offers some major contradictions: digital strategies allow making things more visible yet not necessarily more engaging; they make things more connected but also more likely to enlarge existing inequalities; they facilitate patient empowerment yet are constrained by their socioeconomic capacity. This disjointed evidence highlights the importance of having strong, setting-specific empirical studies that concurrently look at the effectiveness of digital marketing, the behavior of patients, and limitations of health care systems, especially in the developing economies.

Research Objectives (Concise Version)

The concept of digital health marketing has become an important instrument of better patient engagement and control over the use of healthcare services, but the current evidence is still dispersed and context-related (Ventola, 2014; Budd et al., 2020). In order to address these gaps, the current study will seek to:

1. Test how patient engagement is affected by digital marketing of health plans. Previous research indicates that patients could be empowered by means of digital platforms, although the level of engagement differs among populations (Graffigna et al., 2015; Barello et al., 2016).
2. Determine the mediating role of patient engagement on the relationship between digital health marketing and the use of healthcare service. The engagement is considered as an action process that connects online outreach with the adoption of services (Barton et al., 2022).
3. Assess the immediate effect of the digital health marketing interventions on the use of healthcare services. There is both evidence and counter-evidence as to whether appointment adherence with telehealth use is inherently caused by digital tools or not (David and Roberts, 2022).
4. Provide the most impactful elements of digital health marketing (e.g., websites, social media, mobile apps, telehealth promotion, CRM tools). The digital strategies work in various touchpoints but the comparative effectiveness has not been explored (Kotler et al., 2021).
5. Survey demographic variations that can tone down the effects of digital marketing. Adoption patterns are known to be influenced by digital literacy and access (Rao et al., 2021).

RESEARCH METHODOLOGY (EFA USING SPSS)

The Exploratory Factor Analysis (EFA) was done to determine the latent dimensional pattern of the constructs of digital health marketing and patient engagement. EFA should be used at the initial stages of the scale development or when the task is to reveal the latent variables and analyze the patterns of item clustering (Hair et al., 2020). The statistics were analyzed with SPSS Version 26.0 and done in accordance with the psychometric principles.

Participants were recruited using a convenience sampling technique. A sample of 246 respondents was utilized, which is sufficient to provide a good extraction of factors with a minimum ratio of 5-10 participants per item (Kline, 2016). Before analysing the data, missing values, outliers and normality were screened. Products that had high skewness or kurtosis were tested and kept depending on their relevance in theory.

The data needed to conduct this study were gathered with the help of the structured self-administered questionnaire, which was created in order to assess the perception of the respondents towards digital health marketing tactics, patient engagement, and their use of the healthcare services. Health services research also heavily relies on structured questionnaires as they allow such studies to be standardized, limit researcher bias, and make statistical analysis of large samples more possible (Creswell and Creswell, 2018). The scale was a Likert scale (1 = strongly disagree to 5 = strongly agree) which included items derived, with modifications, because of content validity, of validated instruments on digital health and patient engagement (Graffigna et al., 2015; Ventola, 2014).

The survey was carried out through the internet and physical means. The online questionnaire was conducted on the secure digital platforms and distributed through email, WhatsApp, and social media groups to increase access and coverage. The offline data collection was done through the distribution of the printed questionnaires in the outpatient departments, hospital waiting areas and community health centers. A mixed approach works together with online and offline methods to enable higher inclusivity and reduce non-response bias in health studies, particularly in a setting with diverse levels of digital literacy (Rao et al., 2021).

Table 1. Questionnaire Items Used for Exploratory Factor Analysis

Q1	The healthcare provider's website is easy to navigate.
Q2	The website loads quickly and functions smoothly on my device.
Q3	The health information provided on the website is clear and reliable.
Q4	The website's appearance and layout are visually appealing.
Q5	I find it convenient to book appointments through the website.
Q6	The website provides all the essential information I need about services.
Q7	I frequently come across the healthcare provider's posts on social media.
Q8	The social media content shared by the provider is informative and useful.
Q9	I trust the health messages shared on the provider's social media platforms.
Q10	I interact (like, comment, share) with the healthcare provider's posts.
Q11	Social media posts encourage me to consider using the provider's services.
Q12	The mobile health app is easy to use and understand.
Q13	I find the app useful for scheduling appointments or follow-ups.
Q14	The symptom-checker or tools in the app are helpful.

Q15	Notifications and reminders from the app are timely and relevant.
Q16	The app performs reliably without errors or crashes.
Q17	Using the app improves my communication with healthcare providers.
Q18	I am aware that this healthcare provider offers telehealth services.
Q19	Telehealth consultations are convenient for my needs.
Q20	I feel comfortable receiving care through telehealth platforms.
Q21	Telehealth services save me time and travel costs.
Q22	The telehealth process is easy to use and understand.
Q23	I receive personalized reminders for check-ups or follow-ups.
Q24	The emails/SMS messages I receive are relevant to my health needs.
Q25	The digital communication makes me feel cared for by the provider.
Q26	I often act on reminders for screenings or vaccinations.
Q27	Personalized digital messages improve my satisfaction with the provider.
Q28	The CRM-based reminders help me stay consistent with my healthcare needs.
Q29	I actively use digital platforms (website/app) to access health information.
Q30	I frequently use online tools to monitor my health.
Q31	I respond to digital reminders and notifications about my health.
Q32	I regularly schedule or manage appointments using digital tools.
Q33	I feel more involved in my care because of digital health platforms.
Q34	Digital platforms motivate me to take better care of my health.
Q35	I am more likely to book appointments because of digital tools.
Q36	I frequently use telehealth services when needed.
Q37	I follow preventive care reminders (e.g., screening, vaccination).
Q38	Digital communication has increased my visits or follow-ups.
Q39	I am more consistent with my healthcare appointments.
Q40	I use digital tools to coordinate with healthcare providers regularly.

Data Analysis and interpretation:

Table 2. Reliability Statistics

Cronbach's Alpha	N of Items
.804	40

The internal consistency analysis revealed a Cronbach's alpha (α) of .804 for the 40-item scale, indicating an acceptable and robust level of reliability. According to classical psychometric standards, alpha values above .70 denote adequate internal consistency, whereas values exceeding .80 reflect good reliability for research instruments in the social and health sciences (Nunnally & Bernstein, 1994; Taber, 2018). The obtained alpha therefore suggests that the items exhibit coherent inter-item correlations and reliably measure the underlying latent construct(s).

Furthermore, the reliability score indicates that the scale is suitable for subsequent analyses such as exploratory factor analysis (EFA) and structural equation modelling (SEM), as recommended in the methodological literature (Hair et al., 2020). Overall, the findings confirm that the instrument demonstrates sound psychometric properties and can be confidently employed in empirical healthcare research.

Table 3. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.904
Bartlett's Test of Sphericity	Approx. Chi-Square	13030.438
	df	780
	Sig.	.000

The Kaiser- Meyer-Olkin (KMO) and Bartlett measures of Sphericity were used to measure the sampling adequacy and factorability of the dataset. The result of the analysis gave a KMO of .904 that is above the acceptable figure of .80, yet in the excellent range (Kaiser, 1974). This means the patterns of correlation between the variables are not too broad such that they can be easily extracted as valid factors. Large values of KMO indicate

that common variance is high and that factor analysis will probably have identifiable and interpretable latent constructs (Hair et al., 2020).
The Test of Sphericity that was performed by Bartlett resulted in a very significant value 13030.438, $p < .001$, which showed that the correlation matrix was not equal to an identity matrix. This relevance proves that there are sufficient correlations between variables, which satisfies one of the assumptions of doing Exploratory Factor Analysis (EFA) (Field, 2018). Combined, these findings confirm the appropriateness of the dataset to EFA and suggest that there are significant underlying factor structures to be obtained.

Table 4. Communalities

Communalities		
	Initial	Extraction
Q1	1.000	.888
Q2	1.000	.887
Q3	1.000	.856
Q4	1.000	.853
Q5	1.000	.866
Q6	1.000	.885
Q7	1.000	.883
Q8	1.000	.892
Q9	1.000	.895
Q10	1.000	.884
Q11	1.000	.881
Q12	1.000	.902
Q13	1.000	.886
Q14	1.000	.893
Q15	1.000	.895
Q16	1.000	.887
Q17	1.000	.868
Q18	1.000	.896
Q19	1.000	.900
Q20	1.000	.882
Q21	1.000	.879
Q22	1.000	.856
Q23	1.000	.885
Q24	1.000	.871
Q25	1.000	.885
Q26	1.000	.878
Q27	1.000	.880
Q28	1.000	.858
Q29	1.000	.888
Q30	1.000	.897
Q31	1.000	.899
Q32	1.000	.890
Q33	1.000	.887
Q34	1.000	.918
Q35	1.000	.900
Q36	1.000	.894
Q37	1.000	.889
Q38	1.000	.884
Q39	1.000	.879
Q40	1.000	.914
Extraction Method: Principal Component Analysis.		

The proportion of the variance of each variable that is explained by the extracted factors is shown by communalities. In the current analysis, the extraction communalities were between .853 and .918 indicating that a significant amount of each item variation was accounted by the factor solution (See Table 4). Hair et al. (2020) have suggested that a communality should be above .50, which is accepted as acceptable; and a value should be above .70, which means that the items represent the underlying underlying latent constructs very well. All the communalities observed depict that all 40 items in the scale are well answered by the extracted components and they have value in the factor structure.

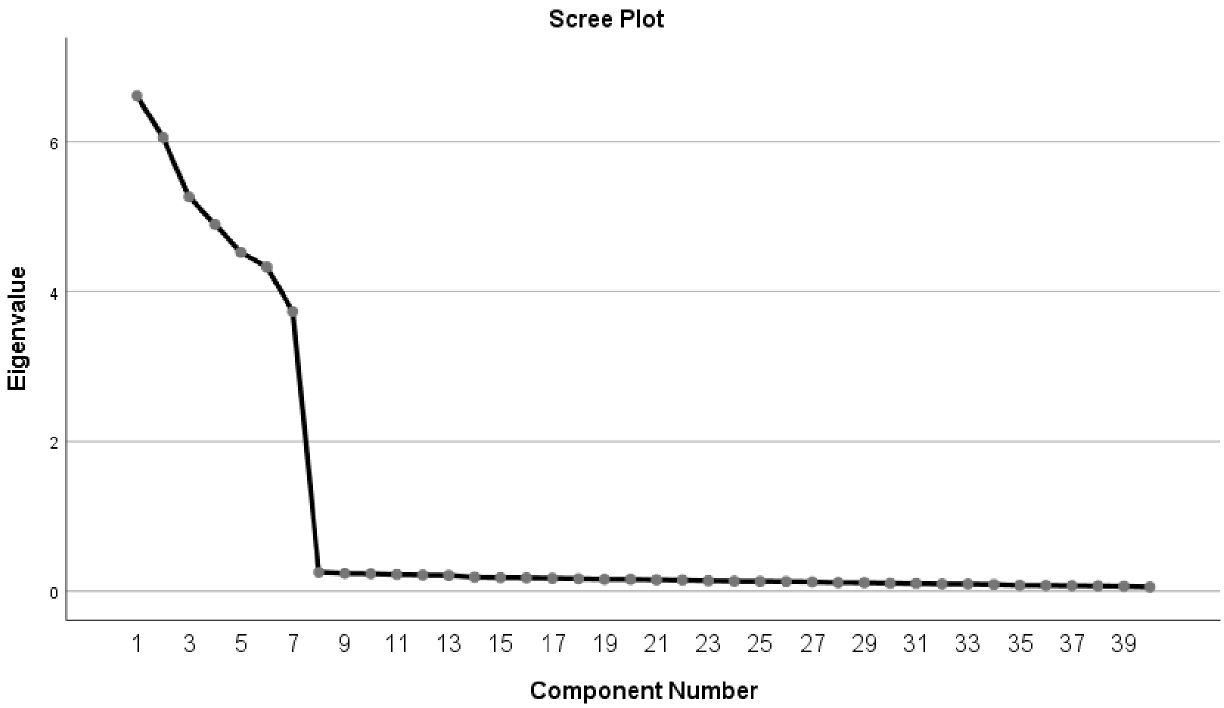
The sufficiency of the sample and factorability of the data is also demonstrated by high communalities, which lend support to the previous finding of the KMO (.904) and the extreme importance of the Bartlett's Test of Sphericity (p <.001). It proves that the dataset can be used in factor analysis, and the factors obtained can be used to represent the underlying dimensions of digital health marketing, patient engagement, and utilization of healthcare services in a reliable way.
All in all, the findings indicate that this measurement instrument has a good construct representation and can be used to carry out further exploratory factor analysis and structural modeling.

Table 5. Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.613	16.533	16.533	6.613	16.533	16.533	5.380	13.451	13.451
2	6.056	15.141	31.674	6.056	15.141	31.674	5.368	13.420	26.871
3	5.263	13.157	44.831	5.263	13.157	44.831	5.319	13.297	40.168
4	4.896	12.239	57.070	4.896	12.239	57.070	5.258	13.146	53.314
5	4.524	11.309	68.379	4.524	11.309	68.379	5.237	13.092	66.405
6	4.326	10.814	79.193	4.326	10.814	79.193	4.431	11.078	77.483
7	3.731	9.328	88.521	3.731	9.328	88.521	4.415	11.038	88.521
8	.249	.623	89.144						
9	.234	.585	89.729						
10	.229	.572	90.301						
11	.219	.549	90.850						
12	.213	.532	91.382						
13	.207	.517	91.899						
14	.184	.460	92.359						
15	.178	.446	92.805						
16	.175	.439	93.243						
17	.169	.423	93.666						
18	.164	.409	94.075						
19	.156	.391	94.466						
20	.155	.389	94.854						
21	.149	.372	95.226						
22	.146	.365	95.591						
23	.138	.344	95.935						
24	.131	.327	96.262						
25	.128	.321	96.583						
26	.126	.315	96.898						
27	.122	.305	97.203						
28	.113	.283	97.486						
29	.112	.279	97.765						
30	.104	.260	98.024						
31	.102	.256	98.280						
32	.095	.237	98.518						
33	.094	.234	98.752						
34	.087	.218	98.971						
35	.076	.191	99.161						
36	.075	.188	99.349						
37	.071	.179	99.528						
38	.069	.172	99.699						
39	.065	.163	99.862						
40	.055	.138	100.000						
Extraction Method: Principal Component Analysis.									

The Total Variance Explained (see Table 5.) shows the findings of the Principal Component Analysis (PCA) displaying the contribution of each of the extracted components to the total variance in the data. The extracted analysis produced seven factors that had eigenvalues above 1.0 and which explained 88.52% of the total variance in the 40-item instrument. The large cumulative variance of this indicates that the extracted factors represent nearly all of the data in the dataset and are a strong representation of the underlying latent constructs (Hair et al., 2020).

The first factor explained 16.53% of the variation, then the second and the third factors explained 15.14 and 13.16, respectively. The sum of rotations of squared loadings obtained by an oblique rotation method gave slightly redistributed variances with the first factor accounting 13.45 percent and the others following the same distribution. Rotated factor loadings increase the interpretation by improving on the clarity of the structure and minimizing on overlaps between components hence making it easy to locate specific constructs (Costello & Osborne, 2005).
Most methodological criteria typically regard the inclusion of a cumulative variance of more than 60 percent to be satisfactory in social science studies (Hair et al., 2020). Thus, the cumulative variance of 88.52 in this study demonstrates a very good factor solution, which has legitimized the use of the instrument in the measurement of multidimensional constructs of digital health marketing, patient engagement, and utilization of healthcare services. These findings give a good background to further confirmatory factor analysis (CFA) and structural modeling.



Scree Plot
The scree plot displays the eigenvalues of all of the 40 items in decreasing order, which gives a visual evaluation of the number of factors to be kept during exploratory factor analysis (EFA). The plot shows that at the seventh component there is an evident elbow hence a distinct drop in eigenvalues. As Cattell (1966) criterion explains, the ones that come before the elbow are meaningful latent variables, and the ones that come after the elbow are not of any significance to add and can be considered trivial (Costello and Osborne, 2005).
This observation is in line with the table of total variance explained and seven factors were found to have eigenvalues above 1 and constituting 88.52 percent of total variance and this observation supports the seven-factor solution. The strong slope of the initial few components shows that most of the data variance is taken by these few elements, the plateau after the seventh component shows that the remaining factors may be noise or less significant variance.
By and large, the scree plot justifies the factorability of the 40-item instrument and visualizes the support of seven distinct factors symbolizing underlying dimensions of digital health marketing, patient engagement, and healthcare service utilization (Hair et al., 2020; Field, 2018).

Table 6. Rotated Component Matrix

	Component						
	1	2	3	4	5	6	7
Q34	.954						
Q31	.942						
Q30	.938						
Q32	.937						
Q33	.937						
Q29	.935						
Q40		.952					

Q35		.944					
Q36		.942					
Q37		.940					
Q38		.937					
Q39		.928					
Q12			.942				
Q15			.942				
Q16			.940				
Q13			.940				
Q14			.938				
Q17			.930				
Q27				.934			
Q25				.934			
Q23				.934			
Q26				.930			
Q24				.928			
Q28				.917			
Q1					.938		
Q2					.938		
Q6					.936		
Q5					.925		
Q3					.921		
Q4					.920		
Q9						.943	
Q8						.941	
Q10						.939	
Q7						.933	
Q11						.932	
Q19							.946
Q18							.942
Q20							.937
Q21							.936
Q22							.921
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.							
a. Rotation converged in 5 iterations.							

An exploratory principal component analysis (PCA) with Varimax rotation produced a clear seven-component solution that maps logically onto distinct dimensions of digital health access, communication, and utilization. Rotation converged in five iterations and item loadings on their primary components were uniformly high (many > .90), indicating a very strong simple structure and low cross-loading for the items presented. The pattern of loadings supports the retention of seven conceptually coherent factors:

1. **Patient engagement and self-management (Component 1).** Items Q29-Q34 and Q31–Q33 (e.g., active use of digital platforms, feeling more involved in care, using online tools to monitor health, responding to reminders, being motivated by digital platforms) load strongly on the first component. This factor reflects an empowerment/engagement dimension whereby digital tools increase patient involvement and routine self-management behaviours.
2. **Healthcare utilization and behavioural outcomes (Component 2).** Items Q35-Q40 (e.g., increased booking of appointments, frequent telehealth use, adherence to preventive reminders, increased visits/follow-ups, appointment consistency, routine coordination with providers) cluster on the second component, which represents downstream utilisation and adherence outcomes associated with digital interventions.
3. **Mobile app usability and functionality (Component 3).** Items Q12-Q17 (ease of use, timely notifications, technical reliability, usefulness for scheduling, symptom-checker utility, improved communication) form a distinct usability/functionality factor, suggesting that perceptions of app quality are empirically separable from broader engagement or utilisation constructs.
4. **Personalized communication and CRM effectiveness (Component 4).** Items Q23-Q28 (personalized reminders, perceived relevance of emails/SMS, feeling cared for, CRM reminders supporting consistency, increased satisfaction) load together, indicating a coherent dimension of personalized digital communication and customer-relationship management effectiveness.

5. **Website quality and informational adequacy (Component 5).** Items Q1-Q6 (website navigability, loading speed, availability of essential information, convenience for booking, clarity of health information, visual layout) comprise a website quality/information factor, distinct from app usability and social media engagement.
6. **Social media engagement and trust (Component 6).** Items Q7-Q11 (exposure to social posts, perceived informativeness, trust in messages, interaction with posts, encouragement to use services) create a social media trust/engagement factor, highlighting the separate role of social channels in shaping attitudes and intentions.
7. **Telehealth awareness and acceptability (Component 7).** Items Q18-Q22 (awareness of telehealth services, convenience, comfort with telehealth, time/cost savings, ease of the telehealth process) constitute a telehealth-specific acceptability factor, distinct from general app or website perceptions.

Taken together, the factor solution demonstrates both **theoretical clarity** and **empirical separation** among constructs related to (a) technology *usability* (website, app), (b) *communication strategy* (personalized CRM, social media), and (c) *behavioural outcomes* (engagement, utilisation, telehealth acceptability). High primary loadings and the absence of problematic cross-loadings suggest the items are well-specified for measuring these latent dimensions.

CONCLUSION

The findings of the exploratory factor analysis (EFA) reveal a rigorous seven-component structure encompassing user interface usability, information clarity, personalized CRM-driven interactions, trust in social media communication, telehealth acceptance, community-based digital engagement, and consequent behavioural outcomes. The factorial solution demonstrates strong internal coherence and provides valuable empirical grounding for conceptualizing digital health as a multidimensional construct. Notably, the clarity of factor loadings and the distinctiveness of component clusters indicate robust psychometric soundness and strengthen the theoretical underpinnings of the emergent model.

Evidence is growing that digital health platforms are more than just transactional intermediaries of technology; they can also be agents of change affecting the continuity and quality of care. Therefore, digital health technologies affect the continuity and quality of care, as well as increase patients' health literacy, empower patients to take charge of their own care, and enhance patients' utilization of telehealth features. More specifically, research suggests that combined with enhanced usability and easy access to timely information about the individual patient, digital health technologies can improve overall patient satisfaction, perceived quality of service, and adherence to medical recommendations (Sahranavard et al., 2023; Gopal & Ramasubbu, 2022). The patterns of interconnection that emerged from these findings emphasize the key functional role of Personalized CRM Communication in supporting relational continuity, agency building and relevance of health information. The results are consistent with past studies that indicate personalization strategies (e.g., appointment reminders, scheduling prompts, and tailored patient education materials) positively increase compliance, encourage proactive decision making, and increase preventive health behaviours (Choi et al., 2021).

The findings also relate to the concept of digital health equity. Providing alternative channels for care delivery through integration of telehealth platforms into customer relationship management (CRM) systems allow underserved communities, as well as other potential health disparities, an avenue towards improved health access by reducing barriers to care. Optimisation of usability and information frameworks have resulted in a greater willingness on behalf of individuals to engage in this form of care delivery which leads to improved connectivity and resiliency for those within an inclusive healthcare system. Ultimately, the results of the exploratory factor analyses provide insight into how the various components mentioned above come together to influence how well an individual utilises digital health services and achieves positive health outcomes.

Recommendations

It would be beneficial for future research to conduct a confirmatory factor analysis (CFA) to reaffirm the seven elements that make up the framework, and to gauge the integrity of its constructs via Composite Reliability (CR), Average Variance Extracted (AVE), and measuring the validity of differences in constructs using the Fornell–Larcker criterion. Once CFA is performed, the researcher may conduct structural equation modelling (SEM) to analyse the directional relationships between the participant's perceptions of usability, psychological factors (for instance, trust and perceived value) and the participant's behaviours when accessing telemedicine (such as utilisation of teleconsultation, continuity of care, and adherence to preventative screening), as referenced in Hair et al. (2019). Longitudinal studies or cross-cultural comparative studies may be particularly useful in further exploring the temporal stability and cultural adaptability of this model.

The use of CRM-based personalization tools by healthcare organizations can improve patient engagement, trust, and retention. Telehealth services that are integrated with mobile notification systems, chatbots, and personalized knowledge dissemination will likely increase the perceived value of digital health products for patients. Further, developing a system for iterative testing and the co-creation of health-related technologies with patients is important to promote inclusivity and access for all patients, particularly those in low-resource settings. Collectively, the recommendations described in this article promote an evidence-based digital healthcare architecture that promotes meaningful involvement of patients, leads to improved results, and strengthens the resilience of healthcare delivery systems (Car, et al., 2021).

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