Data Management Practices, Digitization, and Sustainability of Community Health Programmes in Nairobi County, Kenya

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ABSTRACT

Monitoring and evaluation data from community health programs are essential for their planning, improvement, success, and sustainability. These data can inform implementers, policymakers, beneficiaries, and funders about the progress or lack of it, prompting them to take appropriate action at any stage of the project life cycle. This study examines the moderating influence of digitization on the relationship between data management practices and sustainability of community health programmes. The study is anchored on Technology Acceptance Model (TAM). A positivist philosophical paradigm and a cross-sectional descriptive survey research design to generate quantitative primary data. A Partial Least Squares – Structural Equation Model (PLS-SEM) priori sample size calculator was used to determine a sample size based on all observable variables, including measurement indicators for the moderating variables. The sample comprised 190 community health promoters in Nairobi County. The response rate was 83%. Data analysis was performed using SmartPLS 4. The study results affirmed that the impact of data management practices on the sustainability of community health programmes decreases with digitalisation. The results resonate with the TAM, which posits that the adoption of innovations, such as data management automation, is influenced by perceived benefits and ease of use for users. This study recommends a hybrid data management approach that combines traditional and automated practices to address the transition and the digital divide. The findings of this study can also be used by policymakers and programme implementers to design programmes with greater specificity about where to invest when introducing or scaling up data digitisation, as well as to address contextual factors that contribute to the sustainability of community health programmes.

Keywords: Data management practices, Digitization, sustainability of community health programmes

INTRODUCTION

In the effort to achieve health for whole populations, governments have increasingly focused on community health. Perhaps establishing structures at the household level will help reach the entire population. Developing, expanding, and strengthening community health programmes is argued to be a promising approach to achieving health for all (Perry et al., 2021). Community Health Programmes (CHPs) are also associated with preventing disease progression, reducing healthcare costs, and promoting the population's wellbeing (Khatri et al., 2024). The sustainability of Community Health Programmes (CHPs) is therefore crucial to the communities that benefit from them and to those who implement and fund them. The implementation, scale-up, and sustainability of these programmes seem to depend on data that guide implementers and funders in decision-making and the selection of best practices (Tshuma et al., 2024; Åhlfeldt et al., 2023; Habte et al., 2022; Kirk et al., 2019).

Studies in this area have highlighted that data quality from community health is insufficient (Lee et al., 2021); thus posing a need to invest in data quality to support decision-making on the sustainability of CHPs. Similarly, digitization affects the effectiveness of data management and can play a catalytic role in how the interventions are embraced, adapted, or abandoned (Chirambo et al., 2018). This study was anchored on the Technology Acceptance Model (TAM). TAM posits that acceptance or rejection of technology is influenced by perceptions of its usefulness, ease of use, and, ultimately, the attitude formed around its adoption (Nyimbili & Chalwe, 2023).

In Kenya, CHPs are supported by a legislative framework comprising the Primary Health Care Act, the Digital Health Act, the Facility Improvement Financing Act, and the Social Health Insurance Act, as stipulated by the Community Health Units in the Universal Health Coverage Report (2020). Kenya is committed to achieving the global target of Universal Health Coverage (UHC) by 2030, adopting a community health strategy to help access services for hard-to-reach and marginalized populations (Kenya National Bureau of Statistics, 2020). This resulted in significant investment in establishing community health service infrastructure, supported by government-led legal reform through the Ministry of Health.

An evaluation of community health services in Kenya in 2018 revealed a dire need for investment in CHPs (Ministry of Health, 2020). This evaluation reported three significant gaps in community health services. First, a 41% deficit in Community Health Units (the smallest unit of a Community Health Programme) was identified, reflecting community health service coverage. Second, a 17% gap in the number of recruited Community Health Promoters, who are critical to delivering community health services, including data management. Third, an 85% gap in the number of Community Health Assistants (CHAs) who are crucial in the supervision of Community Health Promoters. In addition to coverage, the quality of data generated by these community health programs has been questioned, posing a challenge to their use in decision-making at various levels (Regeru et al., 2020).

The studies linking DMP and the sustainability of CHPs are hindered by methodological gaps that this study addressed. The study by Donessoune et al. (2023), which aimed to assess the sustainability of TB, Malaria, and HIV programmes funded by the Global Fund, used a small, convenience sample, making generalizability difficult. Furthermore, the study was conducted three years after the intervention, which could have introduced memory bias into the findings. Similarly, a study by Mehra et al. (2020) aimed to identify community- and institutional-level facilitators of programme sustainability, using a qualitative approach. This approach limited the sample size and scope, resulting in a lack of generalizability of the results to other settings. Although a study by Shanmuganathan et al. (2022) focused on non-communicable diseases in Malaysia and employed a mixed-methods study design, the data analysis relied on descriptive statistics, which may not provide the rigor required in research. The methodological gaps identified in the studies by Donessoune et al. (2023), Shanmuganathan et al. (2022), and Mehra et al. (2020) were addressed in this study. The sample for this study was obtained through stratified random sampling. Further, the Partial Least Squares-Structural Equation Modeling (PLS-SEM) technique was used to establish the sample and analyze data. This allowed simultaneous analysis of measurements and structural models and supports the exploratory nature of this study, as supported by Sarstedt et al. (2021) and Ramli et al. (2018). The choice of research methodology adopted by this study, the generalizability of results, and the rigor were guaranteed.

Several studies have been conducted in urban and pre-urban settings of Low-Income and Middle-Income countries, including Kenya, with compelling evidence of the influence of program and contextual-level factors on performance of CHPs (Ogutu et al., 2021). However, the focus of these studies is limited to program performance and not sustainability. This study extended beyond CHP performance to their sustainability, while considering the unique environmental factors in these settings. The studies that came closest to discussing the question for this research are from other countries; the studies by Donessoune et al. (2023), Shanmuganathan et al. (2022), and Mehra et al. (2020) were carried out in Burkina Faso, Malaysia, and the United States, respectively; hence, pausing a contextual gap that this study addressed. Mremi et al. (2022) found a positive link between continuous feedback and sustainability. However, the study was conducted in Sweden's social care sector.

Another contextual gap identified from the literature aligns with the scope, breadth, and depth of CHPs in Kenya. There are fourteen standard areas of focus (Ministry of Health, Division of Community Health Services, Republic of Kenya, 2021). The CHPs in Kenya focus on covering a broad range of health issues at the community level. Most studies on the performance or sustainability of CHPs concentrate on a single disease or health condition (Donessoune et al., 2023; Mehra et al., 2020; Regeru et al., 2020). This fails to recognise the full scope of data handlers' data management work; as a result, the view is limited and may not be representative. This study aims to establish the influence of DMPs on the sustainability of CHPs by addressing all the program focus areas stipulated by the Government of Kenya.

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Based on these existing conceptual, contextual, and methodological gaps, this study potentially addressed the knowledge gaps. Therefore, it sought to answer the research question: What is the moderating influence of digitization on the relationship between data management practices and the sustainability of community health programmes in Nairobi County, Kenya?

LITERATURE REVIEW

The Technology Acceptance Model (TAM), developed by Davis, Bagozzi, and Warshaw in 1989, is one of the most widely used models for explaining the adoption of technology across various fields (Saade et al., 2011). According to Davis (1989), an individual will adopt technology or innovation based on how they perceive its benefits and ease of use, leading to an attitude that determines whether they will adopt it (Nyimbili & Chalwe, 2023). Therefore, the TAM model helps understand how digitization or the use of technology is accepted and adopted and attempts to explain why digitization will be embraced or rejected in managing a firm, organization, or program.

While digitization has the potential to make data management functions easier, faster, and less tedious, it is not always readily adopted, as it is perceived as new, unexplored, and less understood by a portion of its intended audience and users (Nyimbili & Chalwe, 2023). Other factors, such as training, user participation in design and implementation, and the system's features, could also influence the acceptance or rejection of digitization, as noted by Silva (2015), who further explores how system design can influence the acceptance or rejection of the technology. The primary data handlers in CHPs lack adequate participation in the design of, and the use in a range of other essential data management functions (Kenya Community Health Policy 2020-2030).

The applicability of the TAM across contexts can be contested, especially in low-resource settings and in the face of limited technological infrastructure (Zaidi et al., 2020; Bagozzi, 2007); the model fails to account for other aspects that may be institutional or environmental in nature. Despite the reported high penetration of mobile connectivity in Nairobi, a significant portion of the population resides in slums with very low socioeconomic status, compounded by insecurity; these conditions are likely to influence the adaptability of digitization, a factor that TAM has not addressed. This study seeks to establish the influence of digitization on the relationship between DMPs and the sustainability of CHPs.

The relationship between data management practices, digitization, and sustainability of CHPs can be argued based on TAM (Feroz et al., 2020) or systems theory. Systems theory suggests that digitization can be applied to various interconnected and interdependent aspects of data management to enhance system efficiency (Donessouné et al., 2023). This means that different parts of data management practices, such as collection, storage, and analysis, can be digitized to influence the overall data quality. While such practices can be digitized independently, systems theory suggests that to achieve the best results, each subset of a system needs to be addressed. Drawing from the TAM, individuals will embrace digitization only if they find it valuable and easy to use. Digitization can make data management more efficient, improve quality, encourage adaptive implementation, enhance evidence-based and timely decision making of the community health programmes, thus facilitating their sustainability (Dillip et al., 2024; Kansiime et al., 2024; Kaboré et al., 2022; Owoyemi et al., 2022). However, this depends on its availability and the ability of data handlers to utilize it effectively. This section presents the link between data management practices, digitization, and the sustainability of CHPs. This study argues that digitization in data management has the potential to enhance data quality, which is essential for the sustainability of CHPs.

The timeliness and completeness of community health data appear to be exacerbated by environmental factors such as long distances, poor infrastructure, and unhygienic working conditions (Kirk et al., 2021). Some studies attribute the use of MobileApps to improved access and speed to collect, retrieve, and share data; enhanced reporting and monitoring mechanisms of CHP work; reduced workload, advanced personal development, and improved the status of Community Health Promoters in the community they work in (Njororai et al., 2021; Zaidi et al., 2020). There is evidence that the use of mobile devices to collect data and communicate on essential services and processes among community workers has addressed the issues of long distances, poor infrastructure, and sometimes language or cultural barriers, as the data handler does not need to collect data in person (Yang et al., 2021). There was value addition in data quality with digitisation, especially in timeliness, completeness, and consistency of reports (Unkels et al., 2023; Kirk et al., 2021).

On the contrary, a study by Muinga et al. (2020) and Zaidi et al. (2020) found no significant differences in the quality of data collected using electronic gadgets, paper, pen, and blended approaches, apart from the eased burden of carrying the papers. Besides, a few studies have reported negative results from digitization in data management for CHPs. Studies carried out by Zeleke et al. (2019) and Zaidi et al. (2020) highlighted that additional workload and security for mobile devices that capture and store data were a key concern among other factors for the users (Numair et al., 2021). They pointed out that a single accidental error in handling an electronic device can mess up a whole lot of data, and this could lead to a repeat in data collection (Chepkirui et al., 2025). Drawing from the TAM means that data handlers can stay away from mobile devices to avoid security risks for both the devices and themselves. The unfortunate incident of a system failure leading to data loss would result in an additional workload. This issue is already contentious, considering the many tasks a Community Health Promoter is expected to deliver in addition to data management.

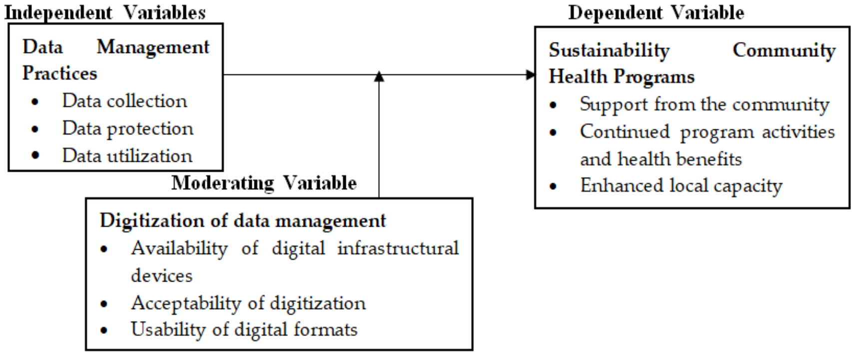
Using technology to collect, share, or report data can potentially minimize the risks of loss or data manipulation associated with the transportation and handling of paper-based data collection and reporting tools. This is because collection and transmission are real-time, and backups and safe retrieval are possible. According to Zeleke et al. (2019), the use of paper-and-pen methods for data collection can result in lost questionnaires due to misplacement and wear and tear, especially when these tools are in transit or in storage. However, despite the benefits of digitization, technical issues such as poor connectivity, unavailability of electronic devices, lack of proper training on their use, or lack of capacity to maintain the electronic devices could affect the quality of data if not well addressed. According to Kreienbrinck et al. (2025) and Zaid et al. (2020), more investment is required to address the behavioral, technical, and organizational challenges of user adoption. According to Tamrat et al. (2022), this requires strategies in change management and strengthening human resource capacity to adopt and sustain the advantages of digitization and its associated outcomes.

The mixed results in the literature present a research gap that this study aims to address. Therefore, this study seeks to establish the potential effect of digitization on the relationship between DMPs and the sustainability of CHPs.

Conceptual Framework

The dependent variable in this study is the sustainability of CHPs, measured by the following indicators: continued health benefits, ongoing program activities, and enhanced local capacity. The independent variable is DMPs, with data collection, data protection, and data utilization as indicators, and the moderating variable: digitization. The indicators for digitization are availability, acceptability, and usability. The conceptual framework illustrates the hypothesized relationship between the variables under study. Figure 1 below shows the relationships among the variables in this study.

Figure 1: Conceptual Framework



RESEARCH METHODOLOGY

Research Philosophy

This study examined the potential influence of DMPs on the sustainability of CHPs and the moderating effect of digitisation and environmental factors on these two variables. This study was based on a positivist paradigm, which was the most suitable for this study, as it aimed to explain and predict the relationship between the study variables, grounded in theory. The paradigm provided hypotheses, which were tested by operationalising the variables and measures identified in the literature to answer the research questions (Jaja et al., 2022). Using a survey to collect quantitative, measurable, and observable data was supported by a positivist approach, in which the conclusions were independent of the researchers' views and the results were generalizable (Park et al., 2020). This theoretical view enabled the researcher to distance themselves from participants' responses (Park et al., 2020). Additionally, an exploratory rather than confirmatory approach, anchored in the PLS-SEM, aligned well with the positivist perspective (Sabol et al., 2023). The findings of this study further inform and clarify existing theories to answer the question of CHP sustainability.

Research Design

This study adopted a descriptive cross-sectional survey design to determine whether a significant relationship exists among variables at a single point in time. The objective was to establish the moderating effect of digitalization on THE relationship between DMP and the sustainability of CHP. The advantage of using the research design is that it is simple, cost-effective, and has a minimal burden on participants (Taris et al., 2021), who are already thought to be overloaded. The cross-sectional survey design also suits the purpose of this study, as it is both explanatory and predictive, and the results can be generalised (Jaja et al., 2022). Using this design, the investigator explored relationships between variables without introducing an intervention or treatment. This study collected and analysed quantitative data to derive conclusions on the research question. Using a quantitative approach, the researcher examined how digitisation was likely to impact the relationship between DMPs and the sustainability of CHPs.

Population of the Study

The population of this study was the Community Health Programmes (CHPs) in Nairobi County, as established by the Kenya Ministry of Health through the Kenya Community Health Strategy (2018-2025). CHPs are an effective way to deliver healthcare and address the significant burden of disease globally (MoH, 2021). In the community health structure, CHPs are implemented through a Community Health Unit (CHU), a level-one health service and the smallest unit. According to the MOH (2021) strategy, a community health unit is a geographical area covering a population of about 5000 people, assigned to 10 Community Health Promoters and one supervisor (also called a Community Health Assistant). The community health units are connected to a health facility where they receive health services in addition to those provided by Community Health Promoters at the household or community level. In this study, the community health unit was the unit of analysis. In Nairobi County, there are 746 community health units distributed across the 17 Sub-Counties (MoH, 2021).

Considering the time and resources available to conduct this study, a sample was selected to represent the 746 community health units. The Community Health Promoters deliver all the preventive, promotional, and essential curative health services to the population at the community and household levels. They are also tasked with collecting, storing, and sharing data on these services and are expected to use the data whenever necessary to respond to emerging issues. Given the mentioned tasks, Community Health Promoters and their supervisors from the 17 Sub-Counties within Nairobi County were identified as the most suitable respondents for this study.

Sampling Techniques

The study population comprised 746 community health units. Since the population is large, a sample of the population was proposed and established through the PLS-SEM. The SEM model has various approaches for determining sample sizes. The use of PLS-SEM to determine sample size was preferred because it can achieve higher statistical power regardless of sample size, supports complex models, and accounts for prediction errors

(Hair, 2022). PLS-SEM has been successfully used in other studies to determine sample size, such as Chirchir (2022) and Odock (2016). In line with SEM, the a-priori Sample Size Calculator for Structural Equation Models was used to compute the sample size based on the number of measurement indicators and latent variables (Soper, 2020). The formula for calculating the sample size is as demonstrated below;

$$\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt.$$

The study involved 12 measurement indicators and 3 latent variables, yielding 15 observable variables. With a medium effect size of 0.3, a statistical power of 85%, and a significance level of 5%, the minimum required sample size for this study, according to Soper (2020), is 152 participants. A minimal non-response was expected in this study, as data collection was conducted in an in-person meeting; therefore, a 20% increase in the sample size is recommended (Bujang, 2021). Hence, the study's sample size was 190. This calculation is similar to that used successfully by other cross-sectional studies, such as Chirchir (2022) and Oredo (2016), which were deemed suitable for the conceptual model. A structured questionnaire with five sections was used to gather quantitative data for this study. The sample size was determined in proportion to the population strata, with the strata in this study being the 17 Sub-Counties in Nairobi County, Kenya.

Diagnostic Tests

Before analysis, data screening was performed to check for missing data, outliers, and multicollinearity. This included frequency, mean, and standard deviation. Then, the variance inflation factor (VIF) was used to test for multicollinearity and investigate the associations between study variables. There was no multicollinearity between the independent variables in this study as had been anticipated. Finally, heteroskedasticity was checked by analysing the residuals and plotting the residuals on a graph to show scatteredness. No heteroskedasticity was detected. A 5% significance level was used for the inferential statistics in this study.

Data Analysis

After the data screening process, which included checking for missing values, multicollinearity, scatter plots, and normality, the researcher carried out descriptive analysis to determine the demographic characteristics of the respondents and the characteristics of the community health units. This was done using SPSS software to measure the mean, standard deviation, frequencies and the mean of the study variables. Then, SmartPLS software from PLS-SEM was used to analyse data and establish the relationships among variables. The PLS-SEM was considered robust, with greater flexibility in analysis considering the following: it allows the modelling of multiple independent variables on the dependent variable, it can account for statistical errors, interactions, and correlations, and it can attain higher statistical power compared with Covariance-based Structural Equation (Hair & Alamer, 2022; Collier, 2020). PLS-SEM was also considered appropriate, due to the exploratory and predictive nature of this study (Hair & Alamer, 2022). PLS-SEM also allowed for simultaneous reliability, validity, and hypothesis testing (Shanmuganathan et al., 2022). PLS-SEM was deemed the most suitable for this study, where the sample size was 190, relatively small for covariance-based SEM. Chirchir successfully used the PLS-SEM statistical analysis technique (Chirchir, 2022). The measurement model was tested to specify the relationship among the variables and their observed indicators. The specification of the structural model and evaluation of the hypothesised relationship were established (Shanmuganathan et al., 2022) to answer the study question. Descriptive analysis will be used to analyse respondents' demographic data using SPSS.

Reliability and Validity Tests

Reliability guarantees consistent and steady results from measuring a research phenomenon (Ahmed & Ishtiaq, 2021). It is the degree to which results obtained by measurements and procedures can be replicated (Bahariniya et al., 2021). The researcher conducted a pilot study to gather valuable feedback on the tool and data collection process before commencing data collection for this study. Internal consistency was established by calculating a Cronbach's Alpha coefficient, which was considered a suitable measure of reliability for Likert scales, as Mohd and Lay (2021) argued. For this study, an internal consistency coefficient of .70 or higher was acceptable (Hair et al., 2022).

Furthermore, principal component analysis was performed to assess the scale's reliability. The researcher aimed for a variance of at least 0.3 for any item considered part of the latent variable (Al-Emran et al., 2019). Composite reliability was used to evaluate the internal consistency of the latent constructs in the model (Al-Emran et al., 2019). Composite reliability was established if the score was more significant than 0.6. The researcher used the Average Variance Extracted (AVE) to establish the model's internal consistency. This study considered any AVE greater than 0.5 acceptable (Fauza, 2022; Al-Emran et al., 2019).

The researcher further assessed the instruments' validity, focusing on content, construct, and criterion validity. Testing content validity ensured that all essential items were included in the study instrument. Experts in community health were consulted to validate the constructs and ensure that the items' interpretation and meaning were well understood. The instrument's criterion validity aligned with the literature and was reviewed by experts, after which it was adjusted in readiness for data collection.

Two criteria were used to evaluate discriminant validity. First, the AVE for each construct was used to compare with its squared correlations with other constructs in the model. Discriminant validity was established if all AVE were higher than the corresponding inter-construct squared correlations (Fornell & Larcker, 1981). Heterotrait-Monotrait statistics were also assessed to establish the discriminant validity (Al-Emran et al., 2019). Discriminant validity was confirmed if HTMT ≤ 0.85 and its confidence interval excluded 1. The structural model was tested for collinearity among the constructs. Collinearity was established if the Variance Inflation Factor (VIF) is not more than 5.

Structural Modelling Estimation and Hypothesis Testing

Structural models were used to understand, predict, and establish the direction of the path, as the study's aim was prediction and exploration. Assessment of the measurements and structural models enabled the researcher to determine the model's predictive capabilities and examine how the constructs relate (Al-Emran et al., 2019). The model's goodness of fit was established using a standard root mean square in line with the PLS-SEM analytic technique (Hair et al., 2022). If the difference between the observed and predicted results was zero, this was considered a perfect fit. However, the emphasis when establishing structural model solutions was more on construct reliability and validity, as recommended in the literature for PLS-SEM analyses (Hair et al., 2022; Shanmuganathan et al., 2022).

The coefficient of determination (R^2) was used to gauge the model's predictive power. Also, marginal analysis was conducted to assess the effect of an omitted predictor on the R^2 values for all dependent variables. In this case, R^2 values of 0.19 indicated weak predictive power, 0.33 moderate predictive power, and 0.67 significant predictive power (Fauzi, 2022). Further, the effect of any omitted predictor on the value of R^2 on the dependent variable (effect, f^2) was established through marginal analysis. The f^2 values of 0.35 signified large, while those of 0.15 and 0.02 indicated medium and small effects, respectively (Shanmuganathan et al., 2022). The researcher then evaluated the model's predictive precision and relevance. Path model predictive precision is acceptable if Stone-Geisser's $Q^2 > 0$ (Sarstedt et al., 2021). In assessing the significance of path coefficients, a t-value> 1.96 or a p-value < 0.05 at the 5% level of significance (2-tailed test) was considered substantial (Chirchir, 2022). In this case, the value zero was not included within the confidence interval.

FINDINGS

The targeted sample size was 190 participants, of whom 176 of the respondents replied. After cleaning the data, 19 questionnaires were not fully answered and were removed from the analysis. Thus, 157 questionnaires were usable, representing a response rate of 83%, which is excellent for the study, as averred by Mugenda and Mugenda (2003).

Sampling Adequacy and Sphericity Test

This section presents sampling adequacy and sphericity tests to determine whether factor analysis is appropriate. Kaiser-Meyer-Olkin (KMO) metrics were employed to determine sample adequacy. Kaiser (1974) stated that KMO levels less than 0.5 are unacceptable. Dimension reduction is assessed using Bartlett's sphericity test. This

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is achievable with p-values < 0.05. All KMO measurements exceeded the specified minimum, with p values < 0.05. This shows that all constructs are statistically significant. The results are shown in Table 1.

Indicators	**KMO Value**	**Approx. Chi-Square**	**df**	**Sig.**
Data Management Practices (DMP_1)	0.880	703.624	10	0.000
DMP_2	0.714	346.033	10	0.000
DMP_3	0.858	527.679	10	0.000
Digitization (D_1)	0.780	252.972	6	0.000
D_2	0.851	511.549	10	0.000
D_3	0.850	762.745	10	0.000
Sustainability of Community Health Programmes (SCHP_1)	0.846	310.816	10	0.000
SCHP_2	0.853	489.603	10	0.000
SCHP_3	0.867	648.751	10	0.000

Table 1: KMO and Bartlett's Test Results

Outer Model Indicator Reliability

The indicator reliability for subconstructs of the three latent variables was evaluated. The results are presented in Table 2. All the indicators of the three latent constructs had outer factor loadings greater than the minimum required level of 0.5. Also, they were all statistically significant at the 5% level. In addition, the indicator reliability of all the indicators was above the threshold of 0.3. Hence, they were all retained for further analysis.

Latent Variable	Indicator	Outer Loading	Indicator Reliability	T statistic	P value
DMP	**DMP_1**	0.870	0.757	12.993	0.000
	DMP_2	0.883	0.780	26.051	0.000
	DMP_3	0.890	0.792	26.761	0.000
D	**D_1**	0.574	0.329	5.677	0.000
	D_2	0.889	0.790	29.728	0.000
	D_3	0.921	0.848	64.068	0.000
SCHP	**SCHP_1**	0.912	0.832	40.556	0.000
	SCHP_2	0.909	0.826	24.757	0.000
	SCHP_3	0.925	0.856	34.122	0.000

Table 2: Reflective Outer Model Results

Internal Consistency Reliability

Composite reliability and Cronbach’s Alpha values were used to determine the internal consistency reliability of the constructs. From the results in Table 3, the composite reliability values for all variables are above 0.8, which is higher than the minimum threshold of 0.7 (Hair et al., 2011). Also, the Cronbach's Alpha for all variables is above the minimum required level of 0.7. Thus, internal consistency reliability is confirmed.

Latent Construct	Cronbach's Alpha	Composite Reliability	AVE
D	0.736	0.867	0.656
DMP	0.856	0.856	0.776
SCHP	0.903	0.905	0.837

Table 3: Cronbach's Alpha, Composite Reliability and AVE Results

Convergent Validity

Convergent validity was assessed using AVE and CFA. The results for CFA are presented in Table 4. The cross-loadings of subconstruct items to their corresponding latent constructs are higher than for other constructs. Also, the AVEs values in Table 3 for the latent variables are all above the minimum required value of 0.5. Therefore, convergent validity is confirmed (Hair et al., 2021).

Indicator	D	DMP	SCHP
DMP_1	0.575	**0.870**	0.616
DMP_2	0.595	**0.883**	0.606
DMP_3	0.602	**0.890**	0.619
D_1	**0.574**	0.332	0.356
D_2	**0.889**	0.535	0.646
D_3	**0.921**	0.685	0.857
SCHP_1	0.722	0.623	**0.912**
SCHP_2	0.721	0.619	**0.909**
SCHP_3	0.792	0.667	**0.925**

Table 4: Confirmatory Factor Analysis Statistics

Discriminant Validity

Discriminant validity was evaluated using two criteria: cross-loadings and the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2014). From Table 4, all constructs load more heavily on their subconstructs than on any other. Additionally, the HTMT ratios in Table 5 were all below the maximum threshold of 0.9, except for SCHP <-> D, which was 0.939. However, discriminant validity is confirmed by the confirmatory factor analysis (Hensler et al., 2015; Hair et al., 2021; Rasoolimanesh, 2022).

	HTMT Ratios
DMP <-> D	0.806
SCHP <-> D	0.939

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SCHP <-> DMP	0.791

Table 5: HTMT ratios

Collinearity for the outer model was determined using VIF and tolerance values. The results are presented in Table 6.

Indicator	**Tolerance**	**VIF**
DMP_1	0.502	1.991
DMP_2	0.455	2.198
DMP_3	0.444	2.254
D_1	0.844	1.185
D_2	0.469	2.133
D_3	0.481	2.081
SCHP_1	0.352	2.842
SCHP_2	0.360	2.777
SCHP_3	0.333	3.001

Table 6: Variance Inflation Factor Outcomes

It was noted that all the VIF values of the subconstructs were less than 5, while tolerance values were larger than the minimum of 0.2. Therefore, there is no multicollinearity in the outer model (Hair et al., 2021).

The collinearity tests for the inner model are displayed in Table 7.

Latent Construct	Collinearity Statistics	
	Tolerance	VIF
D -> SCHP	0.395	2.529
DMP -> SCHP	0.526	1.901
D x DMP -> SCHP	0.470	2.126

Table 7: Collinearity and Tolerance Results

It can be observed that all the VIF scores are below the maximum required level of 5 whereas all the tolerance values are greater than the threshold of 0.2. Therefore, there is no collinearity in the inner model.

Predictive Relevance for Endogenous Variables and Overall Model Fit

The inner model's predictive relevance for the endogenous variable SCHP was 0.740. This Q^2 predictive value is significantly greater than the zero criterion. Predictive significance is therefore confirmed. Using the SRMR statistic, the overall goodness-of-fit of the moderation model was 0.074. This value is less than the required 0.1 upper limit. Thus, it can be concluded that the model is fit.

Target Endogenous Variable Variance

The coefficient of determination, $R^{2,}$ for the endogenous variable SCHP, is displayed in Figure 2. The value is 0.738. Thus, 73.8% of the variance in SCHP is associated with the variance in DMP and D. As per the study by Peng and Lai (2012), R2 values of 19%, 33%, and 67% represent low, moderate, and large explained variance, respectively. Based on these criteria, 73.8% is large. Hair et al. (2021) suggest that effect sizes of 0.025, 0.01, and 0.005 represent more reasonable standards for large, moderate, and low effect sizes, respectively. f^2 for D, D as moderator, and DMP are 0.348, 0.125, and 0.097, respectively, and are all in the range of large effects as represented in Table 8.

Path	f-square	Inference
D -> SCHP	0.348	Large Effect
D x DMP -> SCHP	0.125	Large Effect
DMP -> SCHP	0.097	Large Effect

Table 8: f2 Results

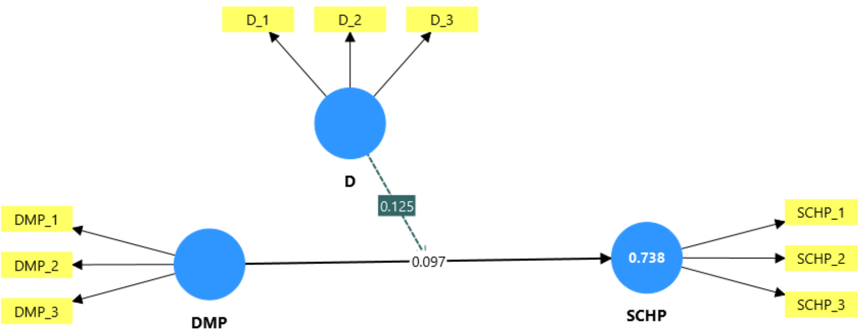

Figure 2: R^2 and f^2 Statistics

Moderation Analysis

The moderating impact of D on the relationship between DMP and SCHP was done using the two-stage approach. Henseler and Chin (2010) proposed that when the main aim is to determine the significance of the moderation effect, the two-stage technique is appropriate, as it also results in a higher level of statistical power compared to the other methods (orthogonalizing and product indicator approaches).

The PLS SEM moderating results are illustrated in Figure 3. The moderating effect has a value of -0.087, while the simple effect of DMP on SCHP is 0.236. These results suggest that the relationship between DMP and SCHP is 0.219 for an average level of D. Nevertheless, if D is increased by one unit, the relationship between DMP and SCHP will decrease by the interaction effect (that is, 0.219 + (– 0.087) = 0.132). In contrast, if D is reduced by one unit, the relationship between DMP and SCHP will increase by the interaction effect (i.e., 0.219 – (-0.087) = 0.306). The graphical presentation is presented in Figure 4.

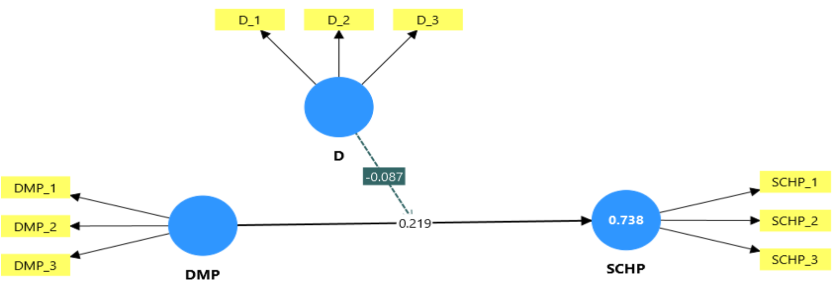

Figure 3: Structural Equation Model having R^2 and Path Coefficients

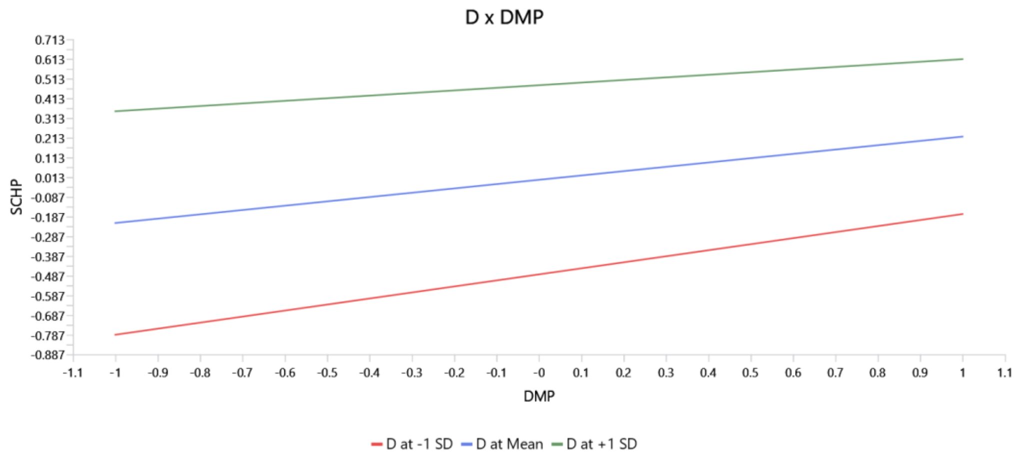

Figure 4: Simple Slope Plot for Moderating Effect

The statistical significance of the moderating effect was tested. From the results in Table 9, Figure 5 and Figure 6, it is observed that the moderating effect of digitization on the relationship between DMP and SCHP is statistically significant (t=2.070, p=0.038).

	Path Coeff.	T Statistic	P Statistic
DMP -> SCHP	0.219	2.959	0.003
D x DMP -> SCHP	-0.087	2.070	0.038

Table 9: Moderating Effect Statistics

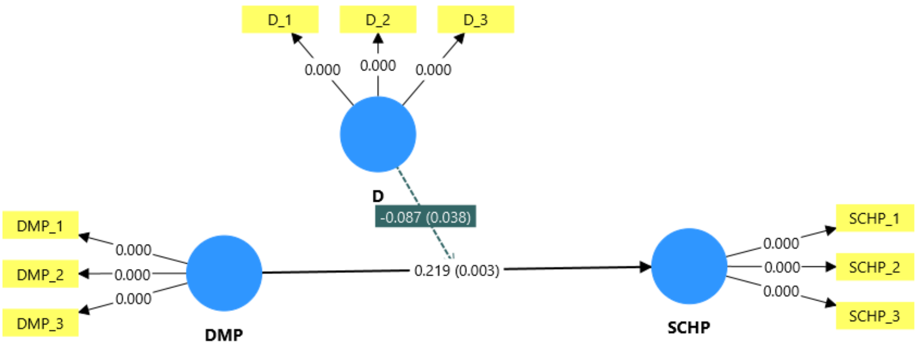

Figure 5: Path Coefficients and P-values Moderation

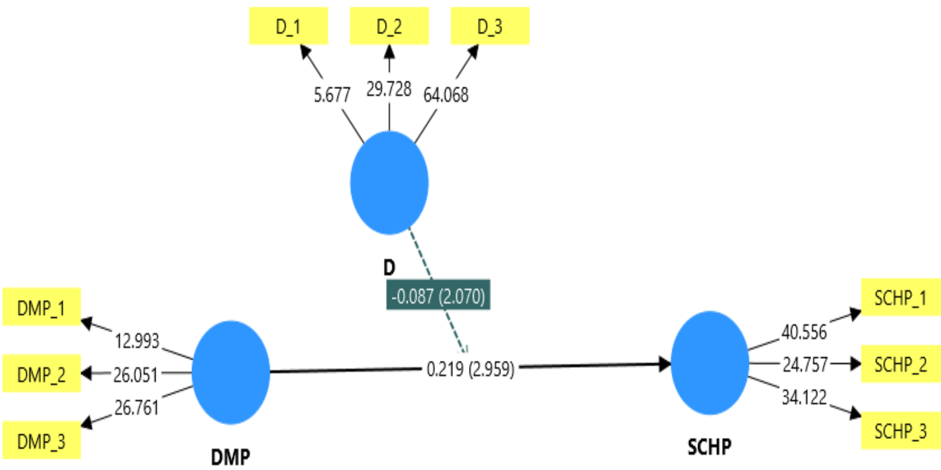

Figure 6: Path Coefficients and T-values Moderation

DISCUSSION OF THE FINDINGS

This study proposed a null hypothesis, stating that digitisation has no significant moderating effect on the relationship between data management practices and sustainability of community health programmes. Using Partial Least Squares Structural Equation Modeling, the analysis found a statistically significant moderate effect with a high model explanatory power and an acceptable model fit. These findings suggest that the impact of data management practices on the sustainability of community health programmes decreases with efforts on digitalization.

This is based on the premise that digitization of data management practices, such as data collection, storage, retrieval, sharing, and use, makes it more efficient and improves the overall quality of data for timely and comprehensive decision-making, hence, improving sustainability of the community health programmes (Dillip et al., 2024; Kansiime et al., 2024). Consequently, when digitization is enhanced, the additional benefit of data management practices becomes insignificant, perhaps because digital systems already streamline data collection, storage, retrieval, sharing, and analysis for effective decision-making. This means that more efforts to enhance data management practices are needed in settings where digitization is unavailable or inadequate, to support the sustainability of community health programmes. It could also mean that with well-automated systems, data management practices are inevitably solved.

The results of this study are consistent with recent studies by Demirci and Yardan (2023), who underscore the foundational role of data management practices in digital health environments, and David et al. (2024), who report that digital tools enhance community health initiatives, but with diminishing marginal returns in over-digitised environments. Similar context-sensitive effects of digitisation have been documented by Rîndașu et al. (2023) and Ribeiro-Navarrete et al. (2023), confirming that digitalization's impact is contingent on complementary organisational capabilities. Blondino et al. (2024), Njororai et al. (2021), and Zaidi et al. (2020) found that digital tools increase data collection speed and accuracy, reduce manual workload, and enhance community health workers' capacity to deliver services effectively. These outcomes are achieved through direct digital entry, voice recordings, and image capture, all of which enable real-time data sharing and utilization. Jeilani and Hussein (2025) further assert that digitized data management eases administrative burden, which supports sustainability by reducing staff burnout and low morale.

However, findings from Blondino et al. (2024), Numair et al. (2021), and Zaidi et al. (2020) also caution that without adequate training, supervision, support, and motivation to maintain high performance, the introduction of digital tools can initially increase workloads, negatively lower morale, and hinder the intended benefits. A different perspective is highlighted by Russpatrick et al. (2021), who point out that digitization is a barrier to performance and sustainability of programmes particularly if there is no proper integration and usability support. This argument is supported by the TAM, which proposes that the adoption of technology is based on perceived benefits and ease of use (Nyimbili & Chalwe, 2023). Hence, in this case, digitization will not be adopted if it is perceived to increase workload or interrupt the status quo.

CONCLUSIONS OF THE RESEARCH

This section presents the conclusions derived from this research, following the testing of the hypotheses designed to explore the variables of this study. Firstly, this research confirms that data management practices such as data collection, protection, and utilization influence the sustainability of community health programmes, resulting in enhanced local capacity and interventions that continue to benefit the host community (Tshuma et al., 2024; Habte et al., 2022; Ceptureanu & Ceptureanu, 2019). The results of this study highlight the critical role of data management practices in maintaining the continuity of community health programmes; if omitted, there would be a marked deterioration. It also confirms that the sustainability of community health programmes benefits from the routine data collected during implementation, thereby assisting with evidence-based planning and context-specific adaptations to emerging challenges, leading to programme ownership, improved health services, and sustainability (Tshuma et al., 2024; Hujala et al., 2021; Popa & Ștefan, 2019). Additionally, this study emphasised the tenacity of traditional, non-automated data management practices in contexts where digital infrastructure is absent or not adequately supported to function optimally, thereby facilitating the sustainability of community health programmes. This is especially beneficial in low-resourced settings where digitization adaptability is challenged by internet and electricity connectivity.

Secondly, this study concludes that digitization had a significant influence on the relationship between data management practices and the sustainability of community health programmes. However, this influence has an inverse effect, meaning that increased digitisation reduces the impact of data management practices on the sustainability of community health programmes. Therefore, in settings where operations are highly automated, there is no need to invest in improving data management practices, perhaps because automation of programmes' operations fundamentally addresses challenges that may occur with manual programme administration, including data management (Owoyemi et al., 2022). Therefore, investments in such contexts should instead address challenges that could hinder the full implementation of digitization, as this has a direct impact on the sustainability of community health programmes, and override efforts to improve data management practices. Additionally, digital interventions in data management practices must be applied multidimensionally, recognising their interdependence and interconnectedness, as elaborated by the systems theory supporting this study (Kaboré et al., 2023; Donessoumé et al., 2023). Therefore, the accessibility, availability, and usability of digital formats, combined with the requisite support such as training, supervision, feedback, and guidelines, are necessary to achieve the programme sustainability outcomes (Bogale et al., 2023).

Implications of the Research

Digital infrastructure availability in this study refers not only to access to mobile phones but also to the connectivity and power supply that accompany them. The TAM assumes adequate coverage of digital infrastructure to support data management practices for the sustainability of community health programmes; hence, it focuses on acceptance and use. Therefore, in a setting where, despite high mobile phone coverage, connectivity and power backup are inadequate, TAM does not predict adoption, which is critical to the sustainability of community health programmes. This study therefore proposes that perceived access to technology is an additional component of the Technological Accessibility and Acceptance Model, such that acceptability and adoption of technology are based on perceived benefit, ease of use, and ease of access. Additionally, this will cover not only the structural support for technology but also explain the cost of using digital infrastructure in low-resource settings, including a substantial segment of the population in this study. This way, both psychological preparedness, as a requisite of human behaviour, and the understanding of prevailing reality will be complemented by the best outcome.

This study has made significant contributions to practice and policy in several ways. The outcome of this study is that there exists a strong relationship between data management practices and the sustainability of community health programmes. This relationship can be enhanced by digitisation and a supportive environment, which is realized through the implementation of policies and programmes. It points to where government leaders should invest in the design and planning of community health programmes to ensure their sustainability. The outcomes inform policymakers of the critical role of quality data in addressing implementation challenges that might hinder the continuity of health programmes.

This study has further demonstrated the need to consider each and all aspects of data management subsets (data collection, data protection, and data utilisation) contributing to the whole system as supported by the system's theory, hence highlighting the need to address all the aspects of data management to attain sustainability of community health programmes. Similarly, as supported by the social ecological theory, this study acknowledges the role of multi-layered interactions towards decision-making, and eventual behaviour among data handlers. According to this study, this could assist the practitioners and policymakers acknowledge and identify capacity needs (such as training and infrastructure provision) for different stakeholders at different levels of data management process. It highlights the aspects to be considered in planning for capacity enhancement to achieve the desired outcomes for the sustainability of community health programmes.

RECOMMENDATIONS

The study has established that, despite high phone coverage in Kenya and most Sub-Saharan African countries, the requisite support for connectivity and power to support functionality is lacking. Therefore, policymakers and funding agencies should prioritise investments in internet and electricity connectivity to support the existing and future efforts in digitalisation. Meanwhile, efforts to support traditional, non-digital data management practices (such as paper and pen) should continue, as this study has established that in settings where digitisation is not fully established, the influence of data management practices on the sustainability of community health programmes is high. This also means that in areas where digitisation is being introduced, programme implementors should focus their efforts on enhancing a hybrid system that combines capacity in the new technology with existing data management practices to ensure a seamless transition. Additionally, implementors should employ gradual digitisation, considering prevailing contextual factors such as connectivity to power and the internet, available resources, and the readiness of data handlers to digitise.

This study used TAM to explain adaptive behaviour to technology. However, this model failed to explain the aspect of perceived accessibility as a key ingredient in its explanation. This study recommends the addition of this aspect to extend the TAM theory; perceived ease of access. Further research can be conducted on the proposed model to expand the body of knowledge. Similarly, the KMT failed to fully explain contextual aspects, considering that knowledge is expected to be from internal as well as external sources in different contexts. This study proposes extending the theory to a context-specific knowledge management framework, encompassing various contexts (for example, well-resourced or under-resourced, analogue or digital technology, formal or informal), to be applied in diverse settings. Future research could focus on the proposed extension of this theory to add to the body of knowledge.

Shortcomings of the Study

This study had a few limitations that could provide opportunities for further exploration by future researchers. It employed a descriptive cross-sectional survey design, utilising a quantitative approach. This data collection method lacks in-depth exploration, such as a qualitative approach, which may have limited valuable insights into explaining the research variables. Additionally, considering the limited time and resources available for conducting this study, the questionnaire was sent to participants via a link to their phones using Google Forms. Although the response rate was high, most did not attempt the open-ended questions that needed typing in digital form. Physical administration of the questionnaire may have provided more robust data, as there would be an opportunity to clarify any issues if need be. Incorporation of other data collection methods could be considered in future research to enhance robustness.

The research also targeted community health promoters (as the primary data handlers) who self-reported on the questions under each variable. This may have led to self-reported bias. Additionally, owing to the cost, this study focused on the experiences of community health promoters (as primary data handlers in a community health programme), which could have left important aspects of data verification or insights from other data handlers at other levels in the system. Data verification at various levels of the data management system in the Ministry of Health is an area that future researchers could focus on.

Proposed Areas for Further Research

Data analysis for this study was conducted using PLS-SEM instead of other approaches, such as covariance-based SEM, as it is an exploratory and predictive approach. This also helped with the analysis of multiple constructs at the same time without the need to collapse them, including those of individual indicators from moderation variables. Future research could focus on other data analysis approaches. The use of a cross-sectional survey design in this study may have resulted in some information being omitted, as this approach does not permit in-depth exploration of the context and reasoning behind the responses provided. Therefore, future research could employ other research designs to triangulate for more comprehensive perspectives.

This research focused on government-sponsored community health programs guided by the national community health strategy. Since other programmes are publicly or privately sponsored, although few, future studies could focus on them all and probably draw comparisons between them. Additionally, this study focused on data management practices from the perspective of community health promoters (community health primary data handlers) and their supervisors. Future studies could expand the study population to include all stakeholders who interact with data management systems, thereby obtaining a more comprehensive view of this data as it reaches different levels in the hierarchy of decision-making. Additionally, verifying the data submitted by community health promoters could provide valuable information on the accuracy, completeness, and timeliness of the data received at that level.

Finally, this study has pointed out a need to extend the TAM to include perceived access to cover the issues of availability of digital infrastructure, including the phone, internet, and power connectivity. Additionally, this study highlighted the need to extend the KMT theory to make it context-specific. Further research can delve into the two theories to expand their scope and apply them to broader issues and multiple contexts.

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