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Sustaining community health programmes through routine data management practices in Nairobi County, Kenya: The role of prevailing environmental factors

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ABSTRACT

Data from community health programmes are essential in informing crucial decisions that shape how such programmes are introduced, evolve, and remain relevant. However, the management of these data is influenced by dominant environmental factors that shape the quality of their outcomes. This paper investigates the moderating influence of environmental factors on the relationship between data management practices and the sustainability of community health programmes in urban settings. A positivist paradigm with a descriptive cross-sectional survey design was employed to collect quantitative data from 157 community health promoters, who serve as primary data handlers for these programmes in Nairobi, Kenya. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyse the data. This study confirms a statistically significant positive relationship between data management practices and the sustainability of community health programmes ($\beta = 0.696$, $t = 6.499$, $p = 0.000$, $f^2 = 0.940$). Further, the study confirms that environmental factors have a statistically significant negative moderating effect on the relationship between data management practices and the sustainability of community health programmes ($\beta = -0.173$, $t = 2.796$, $p = 0.005$). Thus, in settings with fragile environmental factors such as poor physical infrastructure, inadequate data-management policies, and unsupportive sociocultural and economic conditions, investing in data-management practices for community-health programmes is crucial. Therefore, the study urges policymakers and programme implementers to consider prevailing environmental factors and to design context-specific, differentiated implementation frameworks to support the sustainability of community-health programmes.

Contribution/Originality: This study is among the few that investigate the moderating role of environmental factors in the relationship between the sustainability of community health programmes and community data management practices using a PLS-SEM approach. It further examines how each indicator under environmental factors influences this relationship, enhancing the study's scientific rigor.

1. INTRODUCTION

Community health programmes are essential for reaching all populations, including hard-to-reach and marginalised groups, through promotive, preventive, and basic curative health services. Data from these programmes is used to make crucial decisions that shape how they are introduced, evolve, and remain relevant. However, the management practices for these data are influenced by prevailing environmental factors, which sometimes determine their quality and, in turn, influence decisions based on them. This argument is supported by McCool, Dobson, Whittaker, and Paton (2022), who confirm that sociocultural and economic factors are important in influencing the success of data-management practices in sustaining programmes. Therefore, the nexus between high-quality data and the sustainability of community health programmes cannot be overstated, as important decisions at different levels of the healthcare system are informed by health surveillance data, service provision, referrals, and disease outbreaks, among other factors (Kuvuna et al., 2024).

In community health, routine data management tasks include maintaining household registers, documenting community health activities, sharing reports, and engaging in dialogue and action to improve the community's health status (Alhassan & Wills, 2024; Regeru, Chikaphupha, Bruce Kumar, Otiso, & Taegtmeyer, 2020). Environmental factors in this paper refer to the conditions external to the programme that influence the delivery of community health services, including data-related tasks. Such factors include, but are not limited to, sociocultural diversity, infrastructural conditions, economic status, and policy guidelines. These external factors have the potential to influence (positively or negatively) the provision or accessibility of community health services and information (Kane, Radkar, Gadgil, & McPake, 2021; LeBan, Kok, & Perry, 2021). Such environmental factors can facilitate or disrupt the evolution of interventions and their continued relevance (Schaaf, Warthin, Freedman, & Topp, 2020).

In urban informal settings, data collection is further complicated by the presence of immigrants from rural areas and, at times, from other countries, which can create tensions between data collectors and community members who provide information due to differences in language, culture, and sociopolitical affiliations (Karuga et al., 2023). In some cases, such strain is caused by social, cultural, and political differences between the data collectors and those who receive health services or are expected to provide data (Schaaf et al., 2020). Consequently, data access is not guaranteed; data may be incomplete, inaccurate, or delayed. Other factors associated with urban environments, particularly in informal settlements, included, but were not limited to, unsanitary conditions, overcrowding, and insecurity (Bakibinga et al., 2022; Ndu et al., 2022). Additionally, data handlers' economic conditions may create competing livelihood priorities that could compromise data management (Riang'a et al., 2024).

These factors could eventually affect not only the quality and coverage of health services, but also the performance and continuity of these programmes. Ignoring such environmental factors could result in missed opportunities or risk the optimal utilization of evidence to make decisions on programme improvement. Therefore, the objective of this study was to examine the influence of data management practices on the sustainability of community health programmes and to determine how environmental factors moderate this relationship in Nairobi's urban settings in Kenya. In this study, infrastructure conditions, socio-cultural diversity, economic factors, and data management policy were the four measurement indicators used to examine the relationship.

2. LITERATURE REVIEW

Systems Theory can explain the relationship between data management and environmental factors in the effort to achieve sustained community health programmes. The primary goal is to obtain high-quality data to inform decisions towards the success and sustainability of community health programmes (Litvaj, Ponisciakova, Stancekova, Svobodova, & Mrazik, 2022; Phan, Phan, & Trieu, 2022). Multiple interconnected environmental factors, including the political situation, infrastructural conditions, sociocultural diversity, economic status, and existing policies, can influence the quality of data for decision-making, thereby affecting the programme's sustainability. Each subset is considered crucial to ensure the whole system functions properly; disharmony among the parts can influence how an intervention is introduced, implemented, and sustained (Kaboré et al., 2022; Ogundeko-Olugbami, Ogundeko, Lawan, & Foster, 2025), implying that if attention is limited to certain factors, achieving and sustaining programme outcomes may be difficult.

The literature has highlighted several environmental factors associated with suboptimal data quality for decision-making in community health programmes. Strained relationships and mistrust between Community Health

Promoters and the community they serve, as highlighted by Njeru et al. (2021). This could be caused by language barriers, cultural, political, or religious differences, among other issues, in an urban setting (Nyande, Ricks, Williams, & Jardien-Baboo, 2022). Additionally, there can be a strained relationship between community health workers and other health-sector actors at different levels of management, often caused by overload, inadequate training, and supervision, among other factors, which can render suboptimal delivery of health services, including data management (Njeru et al., 2021). Conversely, trust and community support can arise from relationships established and nurtured among community members and service providers (in this case, Community Health Promoters) based on mutual benefit from this interaction (Sowon, Maliwichi, Chigona, & Malata, 2024). This could lead to enhanced utilisation of health services and greater responsiveness to data access requests.

The quality of community health programmes seems to be influenced by the infrastructural conditions, such as unsanitary environments, insecurity, overcrowding, and poor road infrastructure, particularly in urban informal settlements (Bakibinga et al., 2022; Fagbemi, Ubani, Oyetunji, & Ukonu, 2025; Ndu et al., 2022), hence affecting the success and the sustainability of community health programmes. Such hindrances result in delayed, incomplete, or absent data required for timely decision-making, thereby affecting resource allocation and work distribution, and leading to missed opportunities for success and the sustainability of health services in the community (Njeru et al., 2021; Regeru et al., 2020). This requires extensive logistical planning to support data management tasks, including collection, reporting, and protection, to ensure timeliness, completeness, and accuracy for informed decision-making.

Considering social diversity as a measurement indicator in this study, the study findings are explained by the Social Ecological Model. The Social Ecological Model proposes that individuals' behaviours and decisions are influenced by interactions at different levels: individual, interpersonal, community, organisational, and policy (O'Laughlin et al., 2021). This means that an individual or community can decide how to approach data management based on their beliefs (either individually or collectively) about health data management (e.g., privacy and usability), which can affect the programme's overall outcomes. This can be further informed by their sociocultural, political, or religious backgrounds (Frozza, Pinheiro de Lima, & Gouvea da Costa, 2021; Morgan, Stratford, Harpur, & Rowbotham, 2024), which, in turn, affect data management outcomes and the sustainability of community health programmes. Therefore, when designing programmes, implementors should consider barriers and facilitators at different levels of interaction to address or harness them for programme sustainability.

The prevailing economic status of those involved in data management may affect their engagement, particularly when tasks conflict with livelihood activities and incentives are undesirable (Riang'a et al., 2024). In low-income contexts where most Community Health Promoters' primary source of livelihood is wages from unskilled labour, such as domestic work and health service delivery, they are likely to be given low priority. Community Health Promoters are likely to adjust their health service activities to accommodate their daily income-generating activities and to abandon them when attendance conflicts arise (LeBan et al., 2021; Ndu et al., 2022). This is likely to affect the delivery of health services, including community-level data management, resulting in delays in data submission, incomplete data, or no data submitted at all (Regeru et al., 2020). Conversely, in contexts where Community Health Promoters are consistently trained, incentivised, and supported with data management tools, data quality is unlikely to be compromised, thereby enabling programme improvement and continuity.

Data management policies provide guidelines and address the questions of 'what', 'how', and 'when' in handling data at different levels. For community health promoters, policies and guidelines for data management include simple instructions on data collection, storage, and protection, outlining what to capture, how to record, store, and submit it, and the frequency of data submission. However, a lack of or inadequate training is blamed for ambiguity, resulting in mistrust of the data and, consequently, low use (Regeru et al., 2020). The reason for the reported low utilisation of data from the community health programme by community health promoters and their supervisors (Tilahun, Bekuma, Getachew, Oljira, & Seme, 2022). On the contrary, the availability of data management policies can deter investment in data management, especially when they are fragmented (Serge, Mbondji, Humphrey, & Janauschek, 2024), as they may instead confuse rather than guide on what is needed. The presence of data management policies and guidelines alone is insufficient; however, the ability of data handlers to interpret and apply them is paramount. Organisational capacity support for orientation, training, supervision, and feedback on data policy implementation is essential, as reported by Regeru et al. (2020).

Addressing only one or a few of these components may not yield the desired results, as systems theory explains; hence, the proposed systems thinking in the planning, design, and evaluation of these programmes. Systems theory contributes, in part, to viewing and planning for community health programs as a whole organisation (system) with parts (subsystems), without which their performance and continuity would be affected (Midgley, 2003). This perspective is expected to help programme managers 'see the bigger picture' and apply integrated thinking to plan community health programmes. On the other hand, it helps managers understand the interplay among the system's components, their effects on one another, and the programme's overall success (Phan et al., 2022). Planning systems thinking also helps establish a feedback loop to assess the contribution of prevailing environmental factors to the programme's success or lack thereof (Kaboré et al., 2022; Phan et al., 2022). For example, establishing that poor road conditions delay data collection and submission, leading to inaccurate donor reports and affecting how donors make decisions on fund commitments and allocations. This study confirms that the prevailing environmental conditions can influence how data management practices contribute to the sustainability of community health programmes.

2.1. Conceptual Framework

The study's conceptual framework illustrates how variables and measurement indicators interact. The dependent variable was the sustainability of community health programmes, measured by three indicators: continued health benefits, ongoing programme activities, and enhanced local capacity. The independent variable was data management practices, measured through three indicators: data collection, data protection, and data utilisation. Four indicators, namely physical infrastructure, sociocultural diversity, economic factors, and data management policy, were used to measure environmental factors as a moderating variable in the relationship between data management practices and the sustainability of community health programmes. Figure 1 represents the conceptual framework.

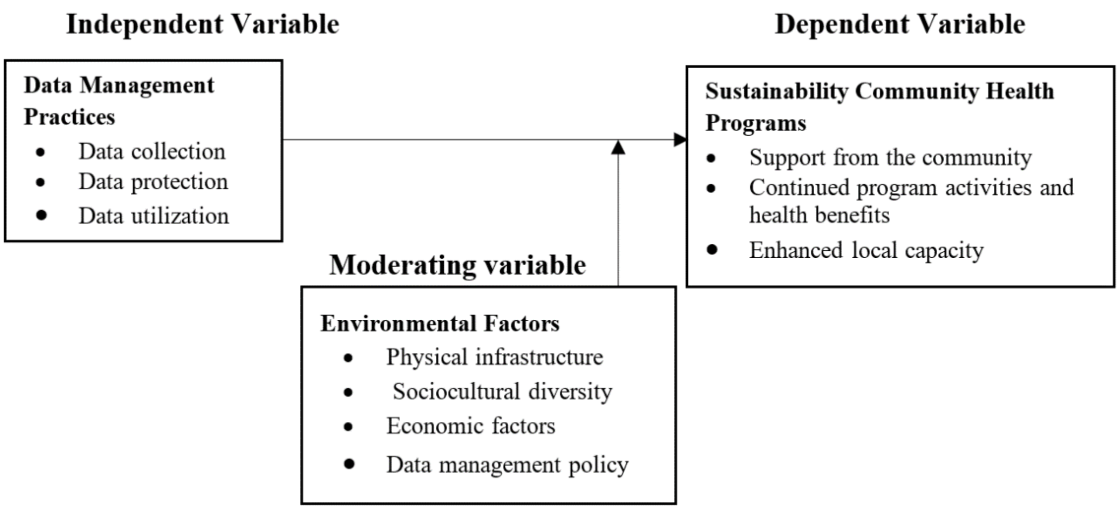

Figure 1. Conceptual model.

3. METHODS

3.1. Research Philosophy

A positivist paradigm guided this study. This aligns with the study's aim of describing and predicting relationships among the study variables using relevant theories. It employed an exploratory rather than confirmatory approach, grounded in PLS-SEM, which aligned well with the positivist perspective (Sabol, Hair, Cepeda, Roldán, & Chong, 2023).

3.2. Research Design

A descriptive cross-sectional survey design was used to investigate how environmental factors influence the relationship between data management practices and the sustainability of community health programmes. The use of this research design ensured the flexibility required for this study, given the resources and time available (Taris, Kessler, & Kelloway, 2021). Using this research design, the investigator explored the relationship between the variables without administering a treatment or intervention.

3.3. Population of the Study

This study involved Community Health Promoters from Nairobi County, Kenya, who are the primary health data handlers and service providers at the community level. Following the Kenya Community Health Policy (2020–2030) and Kenya Community Health Strategy (2018–2025), community health programmes are implemented through the Community Health Units (CHUs), which are at level-one health services and the smallest units in the healthcare system. The CHU has roughly 5,000 people, with 10 Community Health Promoters providing basic health services in line with the government strategy (Ministry of Health, 2021). In this study, CHU is the unit of analysis, with Community Health Promoters serving as the respondents. Community Health Promoters in this study are considered the most appropriate respondents, as they are the primary community health data handlers and providers of promotive, preventive, and basic curative services within the government's health structure.

3.4. Sampling Techniques

In Nairobi County, there are 746 CHUs unevenly distributed across the 17 sub-counties considered in this study as clusters. See Table 1. The respondents from each CHU (cluster) were randomly selected. A sample size of 190 was determined through PLS-SEM. This technique was used to determine sample size owing to its several benefits: it supports complex models that capture relationships among multiple variables, accounts for prediction error as needed, and achieves adequate statistical power regardless of sample size (Hair & Alamer, 2022).

Table 1. Community health units in Nairobi County are distributed across Sub-Counties.

Sub-Counties in Nairobi	CHU distribution	Sample Size
Dagoretti North	56	14
Dagoretti South	44	11
Embakasi Central	27	7
Embakasi East	30	8
Embakasi North	51	13
Embakasi South	43	11
Embakasi West	37	9
Kamukunji	51	13
Kasarani	20	5
Kibra	63	16
Langata	37	9
Makadara	61	16
Mathare	51	13
Roysambu	11	3
Ruaraka	59	15
Starehe	48	12
Westlands	57	15
Total	746	190

The Sample Size Calculator for Structural Equation Models was used to determine the sample size based on the number of measurement indicators and latent variables (Soper, 2021). The sample size was established using the formula below.

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

Assuming a significance level of 5%, a sample size of 152 participants, a medium effect size of 0.3, and 85% statistical power were considered (Soper, 2021). As recommended by Bujang (2021), an additional 20% was added to compensate for anticipated nonresponse, since the survey questionnaire was sent online to study participants by their supervisors during their monthly meeting. Overall, a sample size of 190 was deemed suitable for the study's conceptual models, as supported by Hair et al. (2021). To recruit participants for the study, the sample was distributed proportionally across the 17 sub-counties of Nairobi County, and Community Health Promoters were randomly selected to represent their respective CHUs.

3.5. Data Collection

To ensure that the items in the study instruments accurately measured the intended concepts, content validity and construct validity tests were conducted. The literature was used to guide criterion validity, ensuring that essential items were included. Experts in community health and researchers examined and validated the items' content and construct validity to ensure they best fit the study's research question.

The pilot included only 30 participants from the study sample, which is considered the minimum necessary to adequately represent the sample (Hunt, Sparkman, & Wilcox, 1982). The questionnaire, which included a consent section, was sent to the Community Health Promoters via a link to their phones; most received it and responded during their regular meetings. The leverage of meetings enabled the researcher to address issues with link accessibility and other technical concerns. The data were collected in February 2025.

3.6. Data Analysis

The data analysis for this study included descriptive analysis to determine the demographic characteristics of the respondents and the CHUs. This was done using SPSS to calculate the means, standard deviations, and frequencies of the study variables. To establish the relationships among variables, SmartPLS version 4 software was used, given its robustness and greater flexibility in analysis, including support for multiple modelling, accounting for statistical errors, and achieving higher statistical power compared with covariance-based structural equation (Hair & Alamer, 2022). PLS-SEM was also considered appropriate, given the exploratory and predictive nature of this study, and it enabled simultaneous assessment of reliability and validity and hypothesis testing (Hair & Alamer, 2022; Shanmuganathan, Mustapha, & Wilson, 2022). Considering the relatively small sample size of 190, PLS-SEM was the most appropriate for this study (Hair et al., 2021). To establish the relationship among the variables and their observed indicators, the measurement model was tested. The structural model specification and the evaluation of the hypothesized relationship were established (Shanmuganathan et al., 2022) to address the study question.

3.7. Reliability and Validity Tests

Before data collection, a pilot was conducted to obtain feedback on the tool and validate it. To ensure consistent results, Cronbach's alpha was used to assess internal consistency, a suitable measure of reliability for Likert scales, as argued by Mohd Dzin and Lay (2021). For this study, an internal consistency coefficient of .70 or higher was considered acceptable (Hair & Alamer, 2022).

A principal component analysis was performed, and items were retained if their factor loadings exceeded 0.3 to establish the reliability of the measurement scale (Åhlfeldt, Isaksson, & Winblad, 2023). Furthermore, 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 (Al-Emran, Mezhuyev, & Kamaludin, 2019; Fauzi, 2022).

To establish discriminant validity, firstly, the Average Variance Extracted for each construct was compared with the squared correlations with other constructs in the model, and discriminant validity was confirmed if all AVEs exceeded the corresponding inter-construct squared correlations (Fornell & Larcker, 1981). Secondly, Heterotrait-Monotrait (HTMT) statistics were assessed, and discriminant validity was confirmed if the confidence interval excluded 1 (Al-Emran et al., 2019). Since the HTMT values were ≤ 0.85, discriminant validity was confirmed. The structural model was tested for collinearity among all the constructs. Finally, collinearity among constructs in the structural model was assessed, with collinearity confirmed if the Variance Inflation Factor (VIF) exceeded 5. The VIF and tolerance statistics were computed for both the measurement (outer) and structural (inner) models. It was established that all VIF values were below the maximum threshold of 5, and tolerance levels were above the minimum threshold of 0.2; hence, there was no multicollinearity in the models, which also explains the noninterference of common method bias of self-reporting by Community Health Promoters.

3.8. Structural Modelling Estimation and Hypothesis Testing

This study aimed to explore and predict relationships among variables; hence, structural models were used to establish and understand the direction of these paths. Measurements and structural models were assessed to evaluate the models' predictive capabilities and examine the relationships among constructs (Al-Emran et al., 2019). The empirical equation used to examine this relationship was $SCHP=\beta0+\beta1(DMP)+\beta2(EF)+\beta3(DMP\times EF)+\varepsilon$.

Following the PLS-SEM analytic technique, the model's goodness of fit was assessed using a standard root mean square (Hair & Alamer, 2022). If the difference between the observed and predicted results was zero, this was considered a perfect fit. However, when establishing structural model solutions, the reliability and validity of constructs were given prominence (Hair & Alamer, 2022; Shanmuganathan et al., 2022).

To assess the model's predictive power, the coefficient of determination (R^2) was used, and marginal analysis was conducted to estimate the effect of an omitted predictor on the R^2 values for all dependent variables. 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 researcher then evaluated the model's predictive precision and relevance. In assessing the significance of path coefficients, a t-value > 1.96 or a p-value < 0.05 at the 5% level of significance (two-tailed test) was considered substantial (Hair et al., 2021). In this case, the value zero was not included within the confidence interval.

4. RESULTS

The study response rate was 83%. Of the 190 targeted study participants, 176 responded. However, after data cleaning, 19 were excluded from further analysis due to incompleteness. Thus, 157 questionnaires were usable, which was considered excellent for this study, as contended by Mugenda and Mugenda (2003). The non-response is perhaps due to the self-reporting nature of the online questionnaire or to a limited capacity to use digital tools, since there was no noticeable systematic difference among respondents. Responses from 157 Community Health Promoters, each representing their Community Health Unit (The smallest unit of a Community Health Programme in Kenya), were further analysed to conclude the relationships among the study variables.

4.1. Sampling Adequacy and Sphericity Test

The Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were used to assess sampling adequacy and sphericity. All items in the instruments attained the minimum value of 0.7 and a chi-square of 0.00, thus establishing the relationships among variables and confirming that both factor analysis and PLS-SEM were acceptable, as recommended by Aghimien et al. (2024). Table 2 has the results.

Table 2. KMO and Bartlett's test results.

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
Environmental Factors (EF_1)	0.615	223.983	10	0.000
EF_2	0.778	396.412	10	0.000
EF_3	0.752	204.106	10	0.000
EF_4	0.799	270.985	6	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

Source: Research Data (2025).

4.2. Reliability of Outer Model Indicator

The reliability of the indicators for the subconstructs of the three latent variables was evaluated. The results are presented in Table 3. Outer factor loadings for indicators of all three latent constructs exceeded the 0.7 threshold required and were statistically significant at the 5% level. Additionally, the reliability of all indicators exceeded 0.5, exceeding the 0.3 threshold. Hence, they were all retained for analysis.

Table 3. Reflective outer model results.

Latent Variable	Indicator	Outer Loading	Indicator Reliability	T statistic	P value
DMP	DMP_1	0.870	0.757	12.952	0.000
	DMP_2	0.883	0.780	25.825	0.000
	DMP_3	0.890	0.792	26.933	0.000
EF	EF_1	0.806	0.650	19.515	0.000
	EF_2	0.833	0.694	24.809	0.000
	EF_3	0.769	0.591	18.098	0.000
	EF_4	0.805	0.648	19.756	0.000
SCHP	SCHP_1	0.921	0.848	55.389	0.000
	SCHP_2	0.906	0.821	24.303	0.000
	SCHP_3	0.918	0.843	27.764	0.000

Source: Research Data (2025).

The internal consistency of all the constructs was assessed using Composite reliability and Cronbach's alpha, as demonstrated in Table 4. The composite reliability values for all variables exceed 0.8, which exceeds the minimum threshold of 0.7 (Hair & Alamer, 2022). Cronbach's alpha for all variables exceeded the required level of 0.7. Thus, internal consistency and reliability are confirmed.

Table 4. Results for Cronbach's alpha, composite reliability, and AVE.

Latent Construct	Cronbach's Alpha	Composite Reliability	AVE
DMP	0.856	0.856	0.776
EF	0.819	0.833	0.646
SCHP	0.903	0.907	0.837

Source: Research Data (2025).

AVE and CFA were used to assess convergent validity. The CFA results are presented in Table 5. As a result, it was established that the cross-loadings of subconstruct items to their corresponding latent constructs were higher than for other constructs. Also, the AVE values in Table 4 for the latent variables were above the minimum required value of 0.5. Therefore, convergent validity was confirmed. (Hair & Alamer, 2022).

Table 5. Confirmatory factor analysis statistics.

Indicator	DMP	EF	SCHP
DMP_1	0.870	0.459	0.614
DMP_2	0.883	0.522	0.604
DMP_3	0.890	0.529	0.619
EF_1	0.375	0.806	0.575
EF_2	0.536	0.833	0.696
EF_3	0.354	0.769	0.451
EF_4	0.527	0.805	0.667
SCHP_1	0.623	0.788	0.921
SCHP_2	0.619	0.643	0.906
SCHP_3	0.667	0.643	0.918

Source: Research Data (2025).

From Table 6, all constructs load more heavily on their subconstructs than on any other. Additionally, the HTMT ratios were all below the maximum threshold of 0.9 (Hair & Alamer, 2022). Thus, discriminant validity was confirmed.

Table 6. HTMT ratios.

Latent variables interaction	HTMT Ratios
EF <-> DMP	0.665
SCHP <-> DMP	0.791
SCHP <-> EF	0.807

Source: Research Data (2025).

Collinearity for both the outer and inner models was evaluated, and the results are presented in the following subsections.

It was noted that all VIF values of the subconstructs were less than 5, while tolerance values exceeded the 0.2 threshold. Therefore, multicollinearity in the outer model was ruled out. This information is presented in Table 7.

Table 7. Variance inflation factor outcomes.

Indicator	Tolerance	VIF
DMP_1	0.502	1.991
DMP_2	0.455	2.198
DMP_3	0.444	2.254
EF_1	0.544	1.839
EF_2	0.577	1.733
EF_3	0.566	1.768
EF_4	0.620	1.614
SCHP_1	0.352	2.842
SCHP_2	0.360	2.777
SCHP_3	0.333	3.001

Source: Research Data (2025).

Table 8. Collinearity and tolerance results.

Latent Construct	Collinearity Statistics	
	Tolerance	VIF
DMP -> SCHP	0.550	1.818
EF -> SCHP	0.645	1.551
EF x DMP -> SCHP	0.635	1.574

Source: Research Data (2025).

The collinearity tests for the inner model are displayed in Table 8. All VIF scores are below the required threshold of 5, and all tolerance values exceed the threshold of 0.2. Therefore, there is no collinearity in the inner model.

4.3. Predictive Relevance for Endogenous Variables and Overall Model Fit

The direct relationship between DMP and SCHP was statistically significant with a path coefficient of 0.696 ($t = 6.499$, $p < 0.000$) and (R^2) 48.5%, as displayed in Table 9, Figures 2 and 3.

Table 9. Results of the composite model SRMR.

Original Sample	Sample Mean	Standard Error	T-statistic	P-value
0.696	0.685	0.107	6.499	0.000

Source: Research Data (2025).

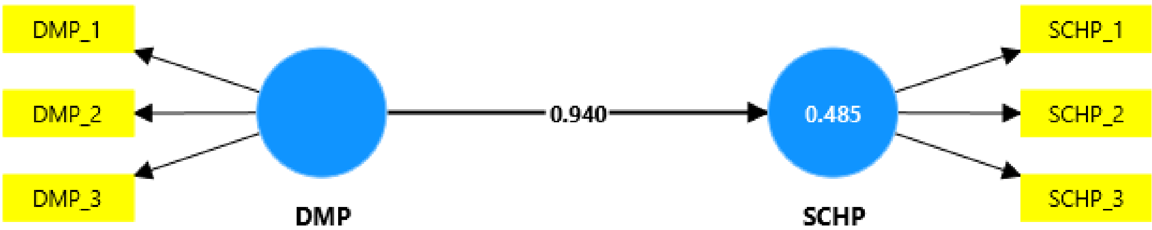

Figure 2. Structural equation model having R^2 and f^2 values.

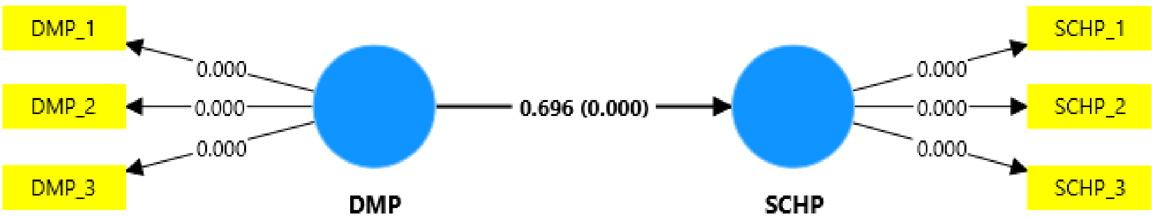

Figure 3. Structural equation model having path coefficients and P-values.

For the environmental factors as a moderator, the inner model's predictive relevance for the endogenous variable SCHP was 0.706. This Q^2 predictive value was significantly greater than the zero criterion. Predictive significance was therefore confirmed. The coefficient of determination (R^2) for the explained variable SCHP is shown in Figure 4. The value is 77.3%. Thus, 77.3% of the variance in SCHP is connected to the variance in DMP and EF, which is large according to Hair and Alamer (2022). The DMP had an effect size (f^2) of 0.107 on SCHP, representing a large effect, while EF had 0.417, indicating a much larger significant effect. This means that DMP on its own is significant, but its significance is much higher when moderated by EF. Thus, a justification of EF as a moderator in this model.

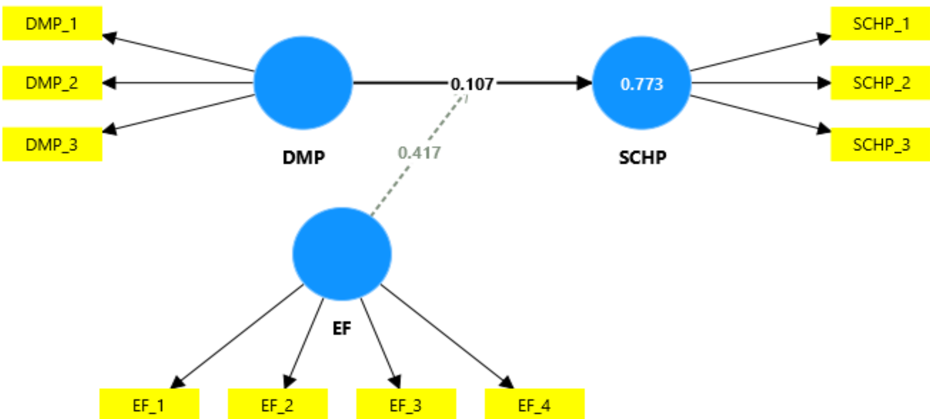

Figure 4. R^2 and f^2 statistics.

4.4. Moderation Analysis

The moderating impact of EF on the relationship between DMP and SCHP was assessed using the two-stage approach, considering that the objective was to establish the significance of the moderation effect, known to yield higher statistical power compared with other methods, such as orthogonalizing and product-indicator approaches (Henseler & Chin, 2010).

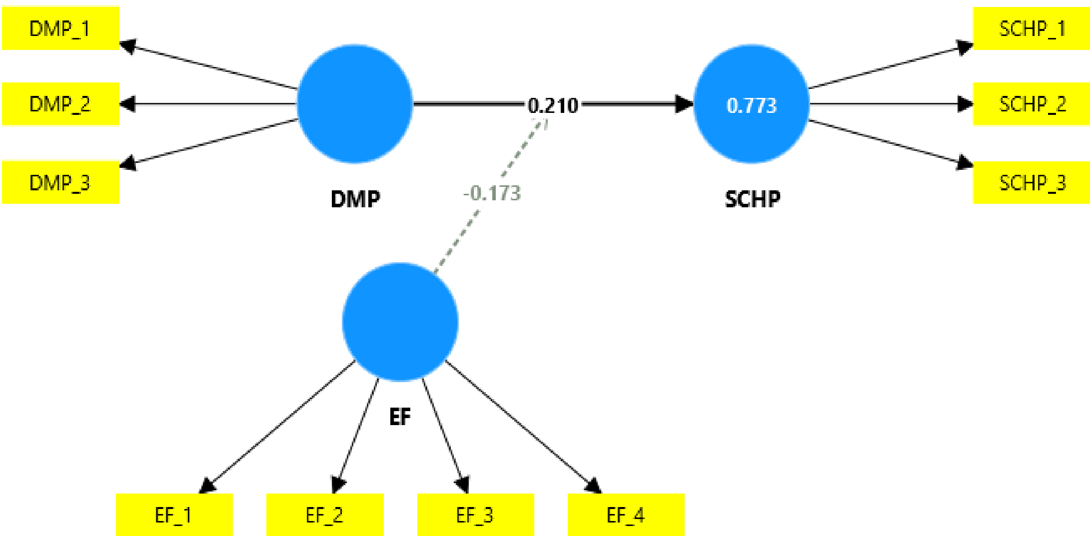

Figure 5. Structural equation model having R^2 and path coefficients.

The moderation results are illustrated in Figure 5, with -0.173 as the moderation effect and 0.210 as the simple effect of DMP on SCHP. Thus, the relationship between DMP and SCHP is 0.210 at the average EF level.

Nevertheless, if EF is increased by one unit, the relationship between DMP and SCHP will decrease by the interaction effect (that is, 0.210 + (–0.173) = 0.037). In contrast, if EF is reduced by one unit, the relationship between DMP and SCHP will increase by the interaction effect (i.e., 0.210 – (–0.173) = 0.383). Figure 6 demonstrates this relationship. This means that as environmental factors improve, the relationship between DMP and SCHP dampens; thus, investment in robust data management practices to improve SCHP is counterproductive.

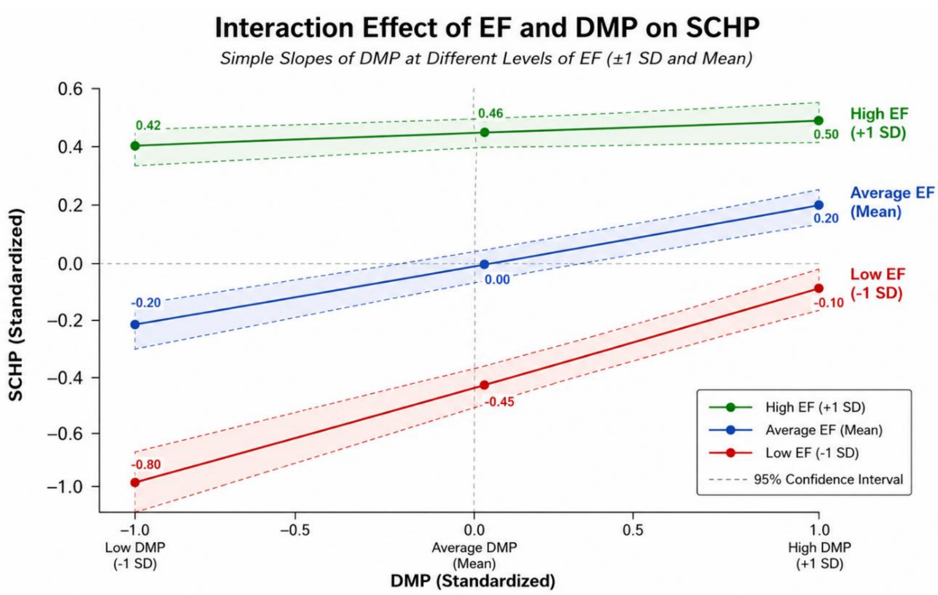

Figure 6. Simple slope plot for the moderating effect.

Note: Higher values of SCHP indicate higher performance. Shaded areas represent 95% confidence intervals. Lines represent simple slopes of DMP predicting SCHP at different levels of EF.

The T-statistic of 2.796 from this model exceeds the 1.96 critical value, demonstrating that the moderating effect is statistically significant, while the p-value of 0.005 is lower than 0.05. This further confirms the significance of the moderating effect, indicating that EF had a significant moderating impact on the relationship between DMP and SCHP. The results are displayed in Figures 7 and 8 and summarised in Table 10.

Table 10. Moderating Effect Statistics.

DMPxEF	Path Coeff.	T Statistic	P-value	f²
Moderating Effect	-0.173	2.796	0.005	0.417

Source: Research Data (2025).

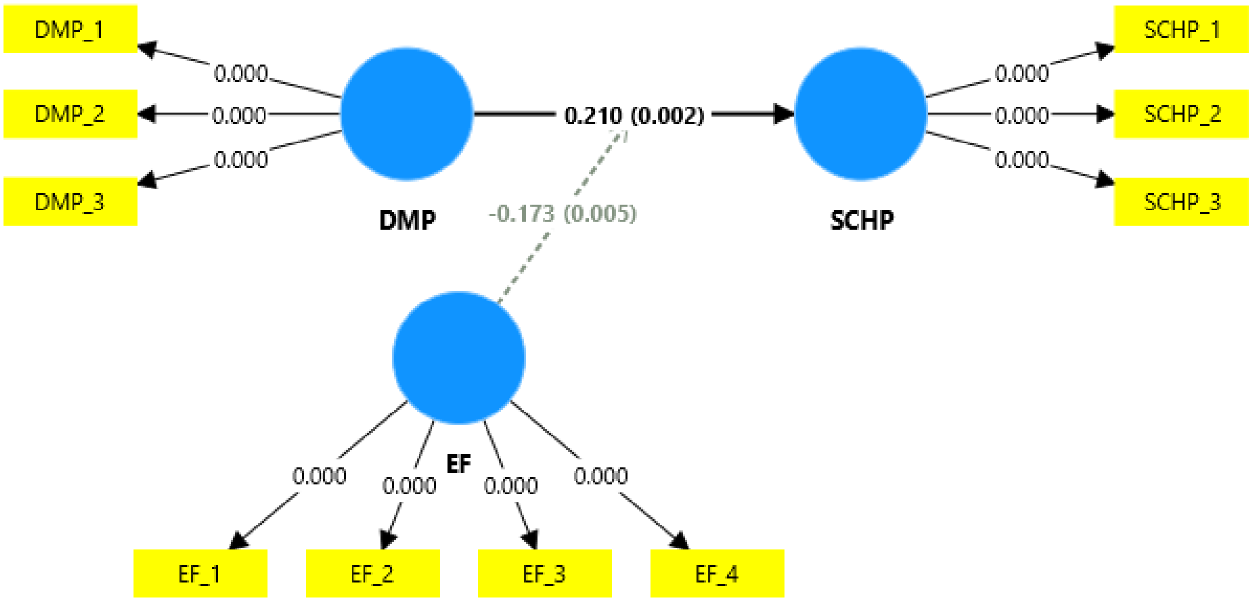

Figure 7. Path coefficients and P-values for overall moderation.

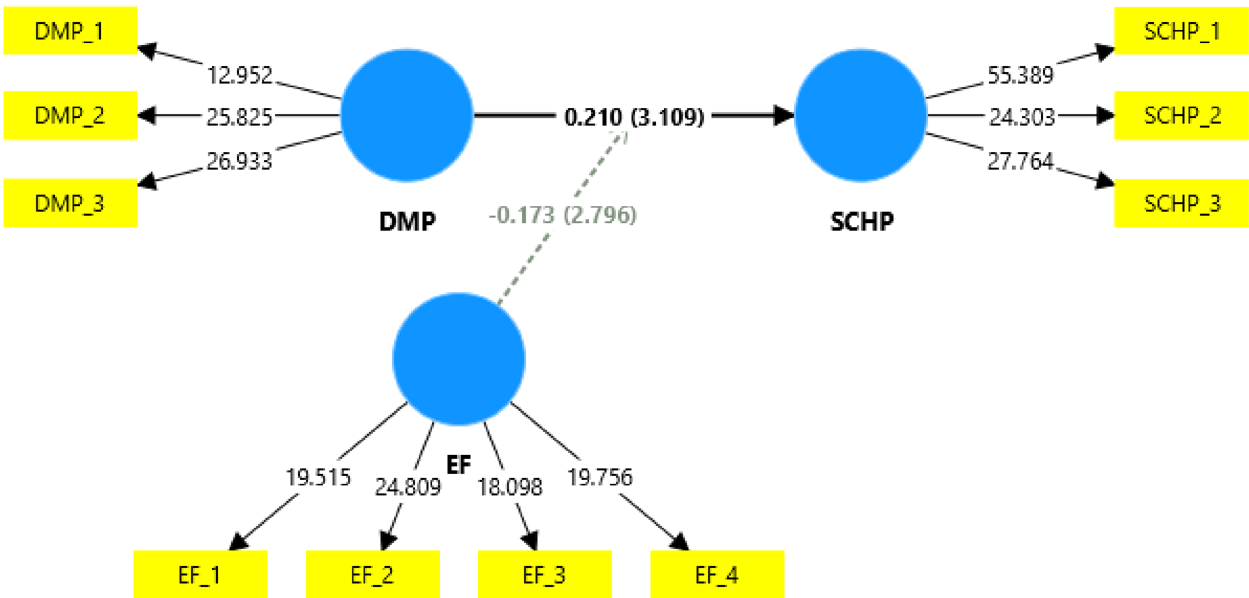

Figure 8. Path Coefficients and T-values for Overall Moderation.

4.5. Moderation by Individual Indicators

The significance of each indicator under the environmental factors was assessed to determine their moderating effect on the relationship between DMP and SCHP. All indicators of physical infrastructure, sociocultural diversity, economic factors, and data management policy had a statistically significant negative moderating effect on the relationship between DMP and SCHP, as shown by the path coefficients in the figures below.

4.5.1. Physical Infrastructure

The path coefficient value of -0.210 (T = 2.135, p = 0.033) is demonstrated by Figures 9 and 10.

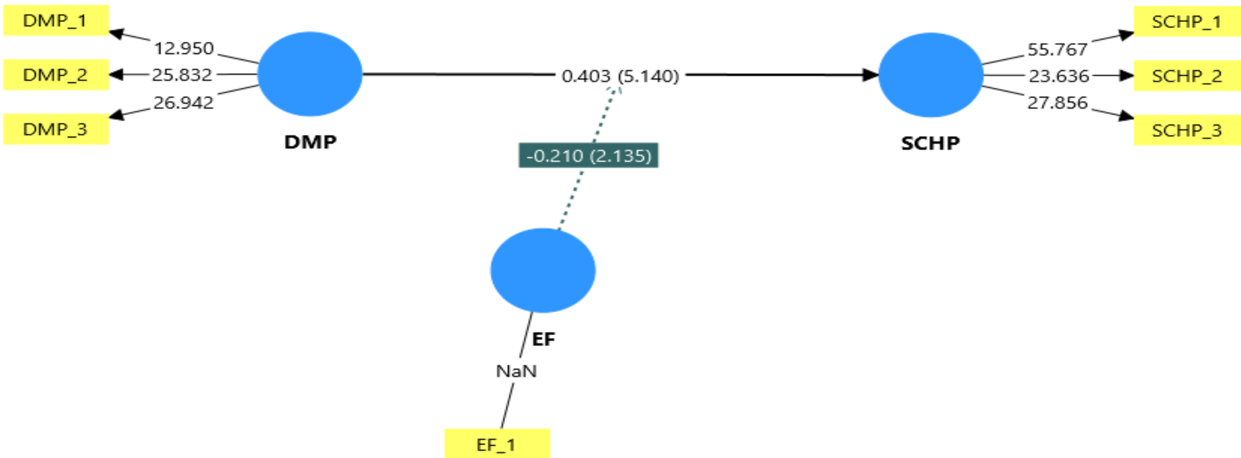

Figure 9. Path Coefficients and t-values for physical infrastructure.

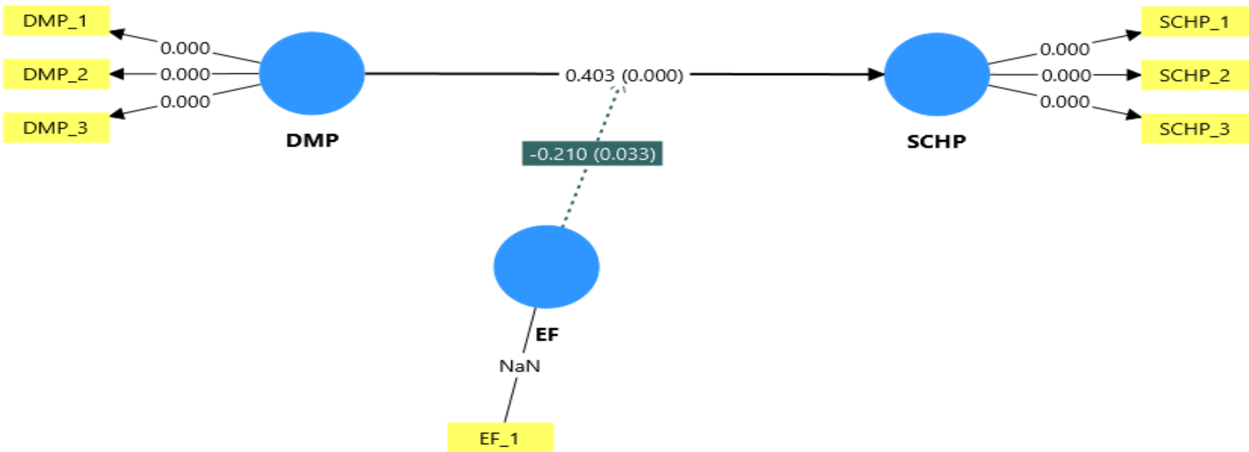

Figure 10. Path Coefficients and p-values for physical infrastructure.

4.5.2. Socio-Cultural Diversity

Path coefficient of −0.150 (T = 2.986, p = 0.003) as shown in Figures 11 and 12.

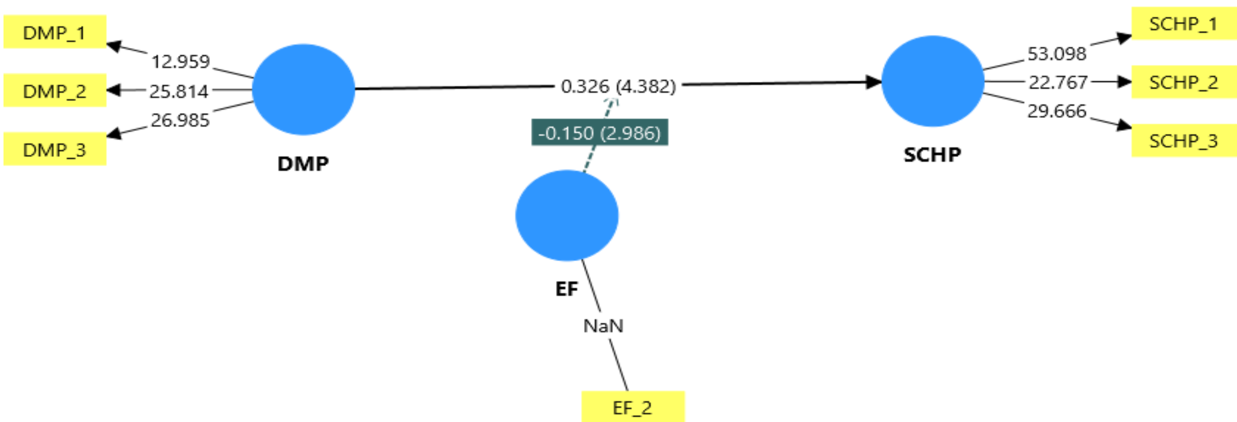

Figure 11. Path Coefficients and t-values for socio-cultural diversity.

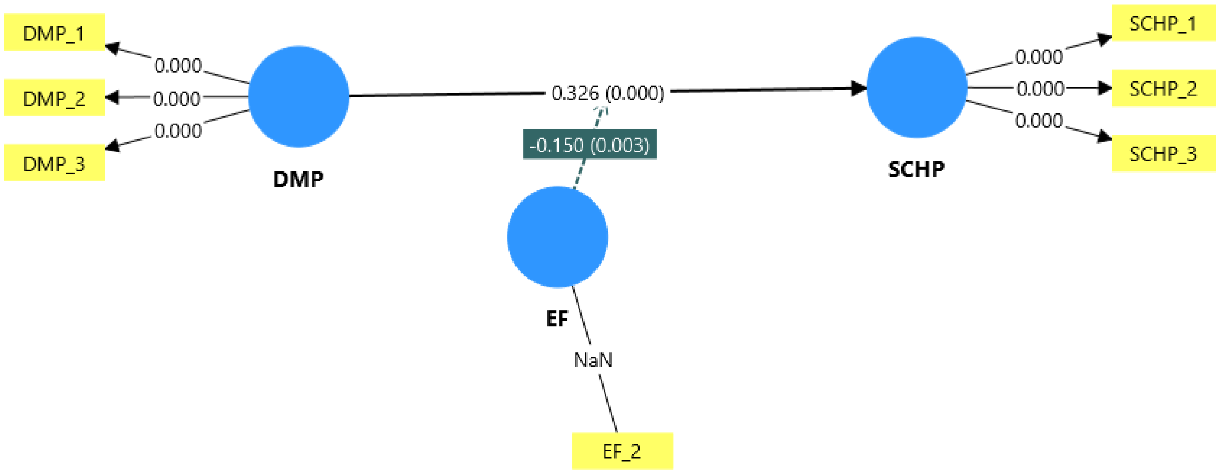

Figure 12. Path Coefficients and p-values for socio-cultural diversity.

4.5.3. Economic Factors

Path coefficient of -0.464 (t = 3.741, p = 0.000) as demonstrated by Figures 13 and 14.

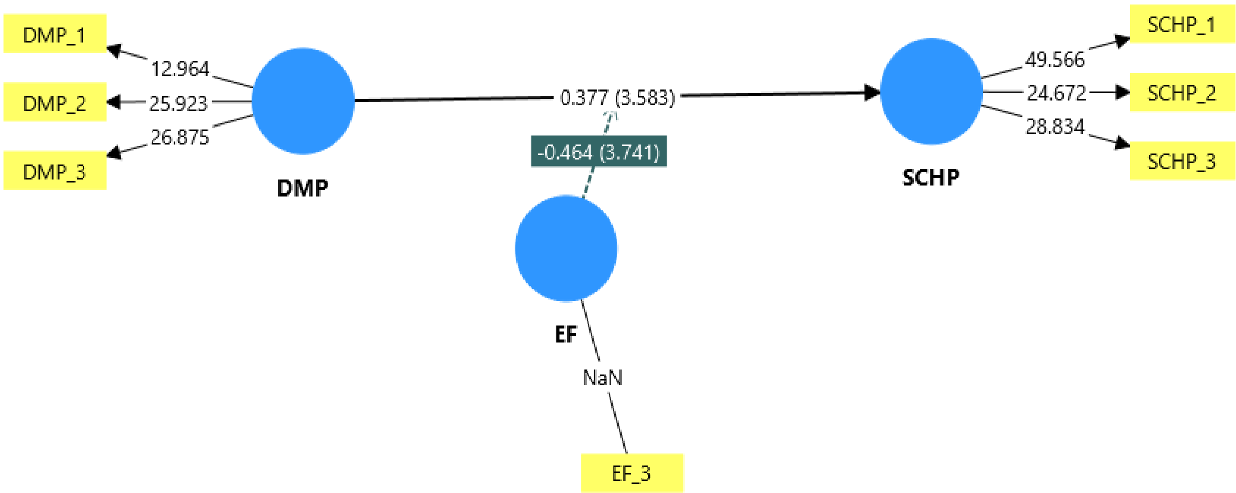

Figure 13. Path Coefficients and t-values for economic factors.

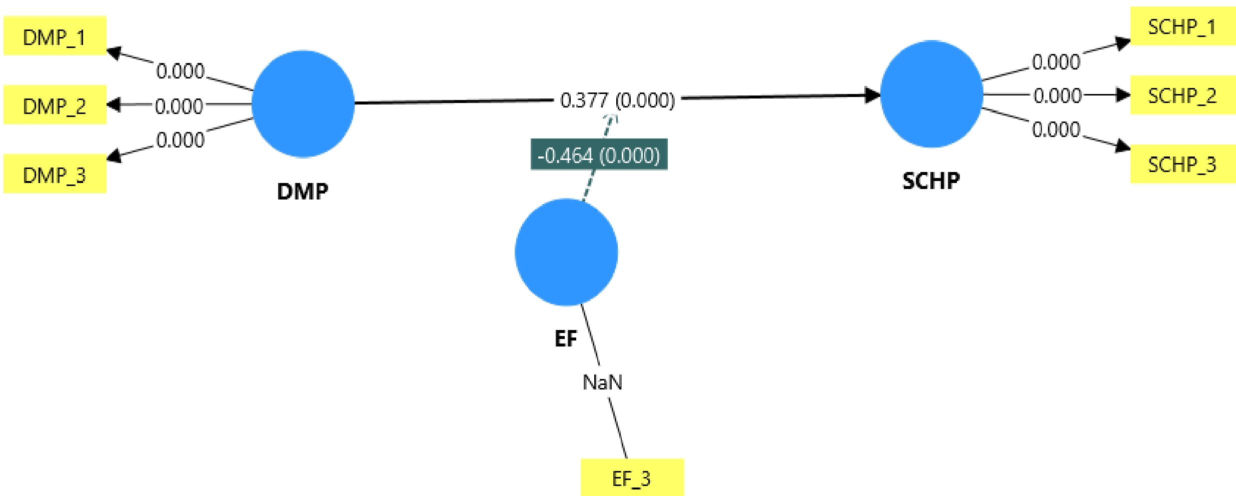

Figure 14. Path Coefficients and p-values for economic factors.

4.5.4. Data Management Policy

Path coefficient of -0.178 (T=2.516, p=0.012) as captured by Figures 15 and 16.

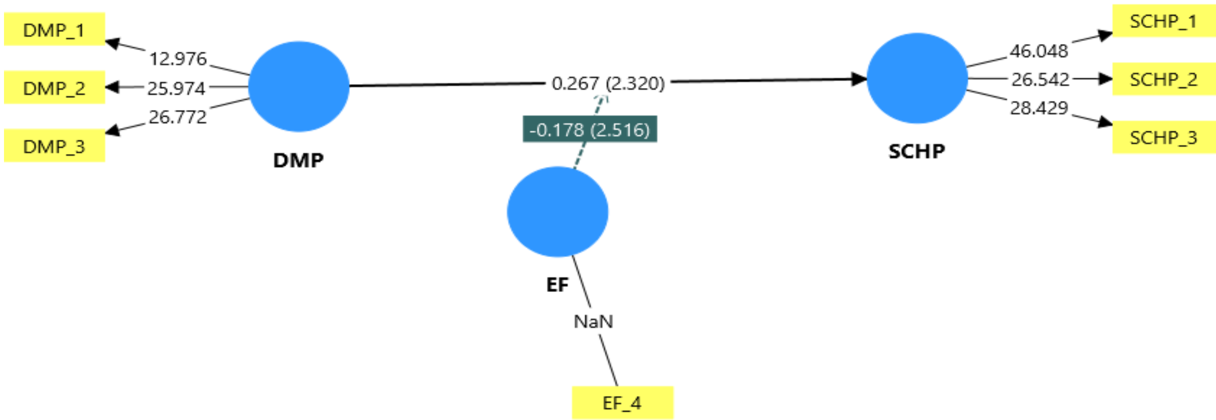

Figure 15. Path Coefficients and t-values for the data management Policy.

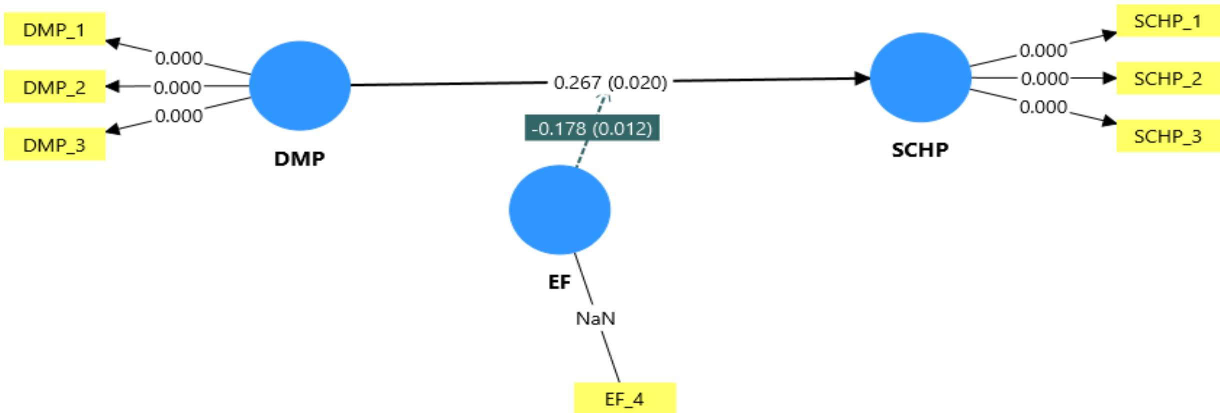

Figure 16. Path Coefficients and p-values for data management Policy.

The physical infrastructure (f^2=0.395), sociocultural diversity (f^2=0.273), economic factors (f^2=0.382), and data management policy (f^2=0.249) are in the range of large effect size, indicating a moderating role of each of the indicators as measures of environmental factors in how data management practices influence the sustainability of community health programmes.

5. DISCUSSION OF FINDINGS

This study established that DMP has a direct, positive influence on the sustainability of community health programmes, confirming findings underscored by other studies on the role of data in decision-making (Amouzou, Faye, Wyss, & Boerma, 2021; Lee et al., 2021; Ogundeko-Olugbami et al., 2025; Phan et al., 2022).

A structural model was developed to assess the moderating influence of environmental factors on the relationship between data management practices and the sustainability of community health programmes. The measurement indicators in this model comprised physical infrastructure, sociocultural diversity, economic factors, and data management policy. A supportive environment means an established infrastructure, such as a road network, telecommunications, community support, and policies that guide data management. The results indicated that environmental factors have a significant and negative moderating effect on the relationship between data management practices and the sustainability of community health programmes. Therefore, the influence of data management practices on the sustainability of community health programmes is contingent on prevailing environmental factors. The negative interaction coefficient implies that in contexts with a supportive environment, the benefits of DMP on SCHP are dampened. Conversely, in settings where these factors are unfavorable, the efforts to sustain community health programmes through data management are crucial. This argument is corroborated by McCool et al. (2022), who confirm that contextual, economic, and cultural environmental factors are important in influencing the success of data management practices in sustaining programmes.

Similarly, the moderation results of the relationship between data management practices and the sustainability of community health programmes by each of the individual indicators of physical infrastructure, sociocultural diversity, economic factor, and data management policies registered a statistically significant negative influence. This means that in settings where the physical infrastructure, such as roads, telecommunications, sanitation, and security, is well established, community support and trust, improved economic conditions, and supportive data management policies mean that efforts to improve data management practices to influence sustainability have diminishing returns. Perhaps this is so, considering that in supportive environments, operations such as data collection, protection, and utilization are already efficient and responsive to the needs of program sustainability.

Improved infrastructure could mean a well-maintained road network, improved sanitation, and automated services, including data management, thereby enabling real-time data availability for decision-making, as observed by Fagbemi et al. (2025). On the contrary, in settings with overcrowding, poor sanitation, a long, poor road network, and non-automated services, efforts to provide health services, including data management, would be difficult. In such contexts, community health workers are expected to collect data using pen and paper and to be provided with protective materials such as gumboots, raincoats, and bicycles for transport and observation, as confirmed by Bakibinga et al. (2022).

Similar to the existing literature (Kavanagh, Hawe, Shiell, Mallman, & Garvey, 2022; Nyande et al., 2022; Schaaf et al., 2020), this study observed that a cohesive community means reduced tensions between community health workers and community members, improved trust and cooperation, thereby facilitating the availability of data for decision-making. In communities where there are marked socio-cultural, religious, or political differences between the community and the community health workers, this may cause tension or mistrust, hampering the efforts to collect and manage the required data to support the sustainability of community health programmes.

In contexts where the economic conditions for community health promoters (managing data at the community level) are considerably high, this would mean that they already have a formal engagement with the government, with a clear scheme of work that is appropriately compensated, thus obligated to perform their tasks, including data management, with diligence and non-conditionally. Conversely, in low-resource settings, community health workers place greater emphasis on their livelihoods than on data management tasks, since their compensation is poor, their work is unstructured, or they must work voluntarily (Riang'a et al., 2024). Data management policies guide those managing community health data on what data to collect and how to handle, share, and use it, in accordance with the laws of the land (Kane et al., 2021), without which achieving data quality for decision-making is difficult. In contexts where these already exist, which are adequate and used as expected, data accuracy, timeliness, and completeness would be enhanced, thus making them dependable for decision-making to support the sustainability of these programmes. In contexts where these policies are unavailable or inadequate, additional support and supervision would be needed to achieve the data quality required to support decision-making, as corroborated in the existing literature (Ogundeko-Olugbami et al., 2025; Regeru et al., 2020).

The findings of this study offer theoretical insights into the systems theory underpinning it. Proponents of systems theory emphasize the interconnectedness, interdependence, and harmonious functioning of subsystems (Donessoune, Sossa, & Kouanda, 2023). First, the sustainability of community health programmes is a product of multiple interdependent variables, including, but not limited to, data management, environmental factors, and the use of digital infrastructure. Secondly, environmental factors are multidimensional, comprising multiple interconnected components such as physical infrastructure, socio-cultural diversity, economic factors, and policy influences, among others, which affect data management practices geared towards the sustainability of community health programmes. Besides, across studies that examine different environmental factors as facilitators or barriers to the functioning of community health programmes, there is consensus that none works in isolation; they must synergise to form a supportive ecosystem for programme sustainability (Åhlfeldt et al., 2023; Caperon, Saville, & Ahern, 2022).

6. CONCLUSION

This study concludes that the effect of data management practices on sustainability community health programmes decreases as improvements in environmental factors, such as physical infrastructure, socio-cultural, and economic factors, and policy on data management practices increase. Therefore, investments towards data management practices particularly need to target areas where environmental factors such as road infrastructure, sociocultural conditions, economic conditions, and policy environments are weak or absent. For instance, the economic insecurity of those handling data (in this case, community health promoters) significantly affects the effectiveness of data management practices in supporting the success and sustainability of community health programmes. The community health promoters will prioritise their income-generating activities, given that community health services receive little or no incentive. Hence, in low-income settings where those responsible for data management lack structured, consistent compensation, investing in improved data management practices would significantly enhance the sustainability of community health programmes (Davis et al., 2024).

Additionally, while infrastructural conditions, data management policy, and socio-cultural factors appear to have significant, modest, and low moderating effects, respectively, on the relationship between data management practices and the sustainability of community health programmes, the influence on economic status is significantly greater. Hence, in low-income settings where those responsible for data management lack structured, consistent compensation, investing in improved data management practices would have a significant positive impact on the sustainability of community health programmes (Riang'a et al., 2024).

6.1. Policy Implication

Thus, in settings with fragile environmental factors such as poor physical infrastructure, inadequate data management policies, and unsupportive sociocultural and economic conditions, investing in data-management practices for community health programmes is crucial. Therefore, investment in robust data-management practices to enhance the sustainability of community health programmes is needed in areas where data handlers' economic status is low, socio-cultural diversity is high, and infrastructure, such as roads and telecommunications, is inadequate. Therefore, this study recommends that programme implementers apply systems thinking, considering multiple factors, not only in planning but also in prioritising resource allocation. The findings of this study have provided insight into the factors to prioritise, given the contextual issues in a programme area, including socio-cultural diversity, physical infrastructure, policy framework, and economic factors.

6.2. Study's Limitations

Data collection for this study involved self-reporting by Community Health Promoters, which may have introduced methodological bias. Future studies can consider using mixed methods to enrich the findings.

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Institutional Review Board Statement: This study was approved by the Institutional Review Board of the Faculty of Business and Management Sciences at the University of Nairobi. At the national level, a research permit was obtained from Kenya's National Commission for Science, Technology, and Innovation (NACOSTI) (Ref. 634110), dated February 14, 2025. Informed verbal consent was obtained from all participants, and all data were anonymized to protect participants' confidentiality.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Disclosure of AI Use: The author has sparingly used AI Grammarly (v1.2.238.1846) for spell-check, grammar, and editing the manuscript as necessary. The work was reviewed and verified by co-authors before submission.

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