Influence of Training and Individual Factors on Knowledge Retention among Community Health Promoters: Baseline Evidence from Nyandarua County, Kenya.

Abstract

Background: Knowledge retention among Community Health Promoters(CHPs)is essential for sustaining effective community health within primary healthcare and Universal Health Coverage. However, post-training knowledge decay is persistent in low- and middle-income countries and Kenya is no exceptional. This study examined the influence of training and individual factors on knowledge retention among CHPs in Nyandarua County, Kenyabased on their entry training received in different years since Kenya's Community Health Strategy introduction in 2006.

Methods:A descriptive cross-sectional design was employed among 1,390 in-service CHPs. The minimum sample size of 311 was determined using Yamane's (1967) formula at a 95% confidence level and 5% margin of error. To enhance representativeness, statistical power and account for potential non-response, this was increased to 482 through cluster sampling across 30 randomly selected Community Health Units. Data were collected using a structured self-administered questionnaire and a knowledge retention test. Analysis was conducted using SPSS using descriptive statistics, bivariate linear regression and regression ANOVA. However, the cross-sectional design limited causal and longitudinal inference and findings were restricted to in-service CHPs in Nyandarua County, limiting generalizability.

Results: Training factors showed a weak but significant positive relationship with knowledge retention ($R = 0.163$, $R^2 = 0.027$; 2.7% variation; $p = .003$), with regression confirming a positive effect ($\beta = 5.590$, $p = .003$). Individual factors showed a very weak, non-significant relationship ($R = 0.077$, $R^2 = 0.006$; 0.6% variation; $p = .168$), with regression indicating no significant effect ($\beta = 0.071$, $p = .168$).

Conclusion: Training factors had a statistically significant but modest influence, whereas individual factors had a minimal influence. These associations suggested that knowledge retention could also be influenced by additional and complex factors beyond those examined. Strengthening training designs, reinforcement mechanisms and broader contextual determinants was recommended to heightenpost-training knowledge retention among CHPs.

Keywords: Community Health Promoters; Knowledge Retention; Training Factors; Health Workforce; Primary Healthcare; Nyandarua County.

1.0: Introduction

The pursuit of Primary Healthcare (PHC), Community Health (CH) and Universal Health Coverage (UHC) globally originates from the Alma-Ata Declaration of 1978, which established the foundation for equitable and effective health systems. Frontline healthcare workers (HCWs) remain central to achieving these goals, particularly in low- and middle-income countries (LMICs) where shortages of trained personnel persist. Effective service delivery depends on HCWs having continuous access to accurate and updated health information. However, ineffective knowledge management can create information gaps that compromise healthcare quality and health outcomes (Rifkin, 2018).

A persistent challenge facing health systems worldwide is the rapid decline of knowledge and skills following training. Conventional approaches such as condensed workshops and one-off training sessions often produce high immediate competency gains but fail to sustain long-term knowledge retention. This results in reduced service delivery proficiency, weakened decision-making capabilities and inefficient utilization of scarce human resource for health (HRH) training investments. The challenge is particularly evident in Sub-Saharan Africa (SSA), where frontline HCWs are essential to maternal, neonatal and infectious disease programs despite substantial post-training knowledge decay. Evidence shows that knowledge retention is shaped by a combination of trainingand individual factors. In these, training quality and pedagogy plays a critical role in promoting deeper learning, memory consolidation and sustained competency (Rogers et al., 2023; Wanjohi et al., 2022; George et al., 2024; Carpenter et al., 2022).

Emerging evidence further indicates that training-related factors significantly but modestly influence knowledge retention outcomes. These include training structure, instructional approaches, duration, content organization, learning materials, language of instruction and opportunities for reinforcement. Learner-centered and interactive training methods enhance engagement and understanding, while poorly structured or lecture-based approaches are associated with faster knowledge decay. In addition, reinforcement mechanisms such as refresher training, mentoring and continuous learning opportunities are critical in sustaining competence and reducing the effects of the forgetting curve (George et al., 2024; Sacks et al., 2020; Elias et al., 2024; Murre & Dros, 2025; Carpenter et al., 2022).

Beyond the training design, individual factors also play a significant role in shaping knowledge retention. These include age, educational attainment, prior training experience, motivation and cognitive readiness, all of which influence how new information is processed and retained. Prior exposure to relevant training and field experience may enhance learning capacity and improve long-term competence. However, these individual capabilities often operate within constrained contexts where HCWs face competing demands such as household economic pressures, caregiving responsibilities, workload intensityand geographical barriers. These factors increase cognitive load, reduce available time for learning and limit opportunities for knowledge reinforcement, thereby contributing to variation in post-training performance among similarly trained individuals (Wanjohi et al., 2022; Kavle et al., 2019; Tsofa et al., 2017; Sacks et al., 2020; Sweller et al., 2019).

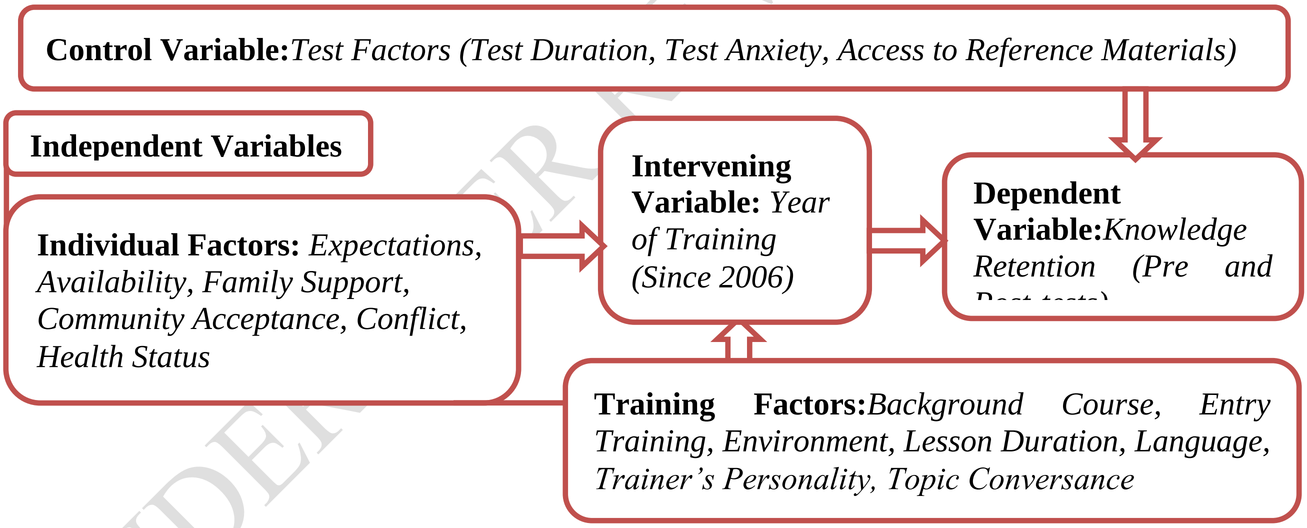
In Kenya, Community Health Promoters (CHPs) constitute the frontline workforce responsible for implementing the Community Health Strategy and extending PHC services to communities (Ministry of Health [MoH], 2021). They are selected from the communities they serve and undergo standardized training before deployment. However, their performance remains inconsistent due to variations in training experiences, individual characteristics and other contextual factors. In Nyandarua County, these variations are further shaped by unique agricultural, socioeconomic and environmental conditions that influence both learning processes and service delivery realities (Wanjohi et al., 2022).

As the first point of contact for many healthcare services, CHPs play a critical role in advancing community health services as a backbone for Universal Health Coverage (UHC), particularly in resource-constrained settings. However, their effectiveness is constrained by weaknesses in training systems and individual-level challenges that affect long-term knowledge retention and performance. Evidence indicates that traditional one-time training approaches are insufficient for sustaining competency, highlighting the need for continuous learning and reinforcement mechanisms to maintain knowledge over time (World Health Organization, 2018; Elias et al., 2024; Rogers et al., 2023).

Despite substantial public investment in CHP training, concerns remain regarding the sustainability of acquired knowledge and skills. Reliance on massed training approaches and limited post-training evaluation has contributed to uncertainty about the factors influencing long-term knowledge retention. Since the formalization of the Kenya Community Health Strategy in 2006, systematic assessment of CHP post-training knowledge retention has been limited, leaving policymakers and training planners with insufficient empirical evidence to guide effective interventions (George et al., 2024; Wanjohi et al., 2022). Consequently, training programs continue to be implemented without adequate understanding of how training and individual factors interact to influence sustained learning outcomes, potentially reducing the effectiveness of training investments (Carpenter et al., 2022; Rogers et al., 2023).

This study is anchored on Baldwin and Ford's Transfer of Training Model, which posits that training outcomes are influenced by the interaction of training design, trainee characteristics and the work environment, although the latter was not examined in this study (Wanjohi et al., 2022; Rogers et al., 2023; Sweller et al., 2019). The model further emphasizes that knowledge acquisition and retention are shaped by both the quality of training and learner attributes, with reinforcement playing a critical role in preventing knowledge decay over time (Elias et al., 2024). Guided by this framework, the study examines the influence of training and individual factors as the independent variables and knowledge retention as the dependent variable among the CHPs in Nyandarua County. While test factors were a controlling variable, year of entry training was an intervening variable (Figure 1.1). This hoped to generate evidence for supporting targeted, adaptive and sustainable training interventions.

1.1: Conceptual Framework



Source: Author, 2026

Figure 1.1 aboveillustrates the relationship between independent, dependent, intervening and control variables in the study.

2.0 Materials and Methods

2.1: Study Design

This study employed a descriptive cross-sectional design to assess retained knowledge from the entry training among the in-service CHPs recruited since the formalization of Kenya's Community Health Strategy in 2006. The design enabled the assessment of knowledge retention at a single point in time using quantitative methods.

2.2: Study Area and Population

The study was conducted among the in-service CHPs in Nyandarua County, Kenya. The target population comprised of all theretained (N = 1,390)CHPsofficially registered within the County Department of Health Services. The retained CHPs were 36.8% of the original workforce, which meant that 63.2% had already dropped out and were therefore inaccessible for interview.

2.3: Sample Size Determination

The sample size was determined using Yamane's (1967) formula for finite populations, yielding a minimum sample size of n = 311 at a 95% confidence level and 5% margin of error:

$$n = \frac{N}{1 + N(e)^2} = 311$$

Where n was the desired sample size, $N$the target population (1,390), and e (0.05) the degree of precision at a 95% confidence level (CI) and a 5% margin of error.This approach was appropriate for finite populations because it provides relatively stable and precise estimates (Adam, 2020; Frost, 2024).

2.4: Sampling Procedure

A cluster sampling approach was applied across all 25 wards of Nyandarua County by selecting one Community Health Unit (CHU) per ward. To enhance representativeness, statistical power and compensate for potential non-responsiveness, an additional CHU per sub-county was randomly selected. This resulted to a total of 30 CHUs and an expanded sample size of n = 482 respondents.Within each selected CHU, a census-by-cluster approach was used whereby all CHPs attending mandatory monthly meetings during the data collection period were invited to participate. Larger samples improve statistical precision, reduce sampling error, increase statistical power and enhance reliability. However, standard formulas may not fully account for population heterogeneity in complex field settings (Sathyanarayana et al., 2024).

2.5: Data Collection Instruments and Procedures

Data were collected using a structured self-administered questionnaire and a knowledge retention test. The questionnaire captured training and individual factors. The knowledge retention test assessed knowledge retention levels among the respondents.

2.6: Validity and Reliability

Content validity was ensured through expert review using standardized checklists and alignment of the instruments with the national Community Health Promoters (CHPs) training manual. The tools were pretested in Community Health Units (CHUs) located at the periphery of the study area that were not included in the final sample. Face and construct validity were strengthened through expert evaluation and pretesting. Reliability of the questionnaire was assessed using Cronbach's alpha coefficient, yielding values of α = 0.78 and α = 0.74 for training and individual factors, respectively. An alpha coefficient of 0.70 or higher is generally considered acceptable for internal consistency (Frost, 2021).

To enhance reliability and minimize measurement bias during knowledge assessment, standardized testing procedures were applied. All respondents completed the knowledge retention test within the same duration (20 minutes) and during the same data collection period across the county. Participants were informed that the assessment was solely for research purposes and would not result in any follow-up actions or negative consequences, thereby reducing test anxiety. In addition, access to learning reference materials, including books and mobile phones, was prohibited during test administration to ensure uniform testing conditions.

2.7: Quality Control and Bias Reduction

Internal validity was strengthened through random selection of CHUs across all wards, standardization of data collection procedures and uniform administration of assessments. Participant blinding to test content prior to assessment and assurances of confidentiality were used to reduce response and test anxiety bias.

2.8: Data Management and Analysis

Data were cleaned, coded and analyzed using SPSS version 25. A total of 320 questionnaires were completed and analyzed, representing 102.9% of the minimum sample size (n=311) and 66.4% of the expanded cluster sample (n=482). Descriptive statistics were used to summarize independent variable characteristics.Bivariate linear regression was used to examine the relationship between independent and the dependent variables, with β coefficients indicating the strength, direction and significance of associations. Regression ANOVA (F-test) assessed overall model significance by testing whether predictors jointly explained variation in knowledge retention relative to a null model. Although useful, these methods may have increased the risk of overfitting, potentially reducing generalizability and predictive validity (Frost, 2023).

2.9: Variable Transformation

Likert-scale responses for the independent and dependent variables were transformed into composite indices by aggregating related items. This improved measurement reliability and enabled quantitative analysis by approximating continuous variables suitable for regression techniques. However, this approach may have reduced item-level detail, masked multidimensional constructs and assumed equal weighting of items (Koo & Yang, 2025).

2.10: Statistical Considerations

Regression analysis was appropriate for this study as it allows identification of extreme observations and assessment of their influence on model estimates while distinguishing errors from valid outliers. However, it is limited by statistical assumptions, sensitivity to outliers, mostly focusing on association rather than causation with the risk of overfitting (Varin & Panagiotakos, 2019).

2.11: Methodological Triangulation

Methodological triangulation was achieved through the combined use of regression analysis and regression ANOVA. This strengthened robustness, credibility and inferential strength by integrating association testing and model evaluation. However, this approach may have introduced analytical complexity, differing statistical assumptions and potential Type I error inflation if not properly controlled. Nevertheless, it enhances confidence in findings when rightly aligned with the study objectives (Arias, 2022).

2.12: Delimitations of the Study

This study was deliberately confined to the CHPs operating within Nyandarua County, Kenya. As such, the findings are context-specific and reflect the training environment, health system structure and socioeconomic conditions unique to this county. While this enhances contextual depth and internal validity, it limits generalizability to other counties or national-level CHP populations unless where the contexts are similar.

The study focused exclusively on CHPs who were actively registered and available during the data collection period, excluding those who had exited the program. Consequently, the results may not represent the experiences of CHP dropouts or absent CHPs who did not attend the manadatorymontly meetings during data collection.

In addition, the study employed a quantitative design using structured questionnaires and a knowledge retention test. Qualitative dimensions such as lived experiences, perceptions of training effectiveness and contextual barriers to learning were not explored.

Finally, the analysis focused on training and individual factors as predictors of knowledge retention. Other potential determinants such as organizational support, supervision quality and health system infrastructure were not included in the analytical model. This scope restriction was necessary to maintain analytical clarity and statistical focus.

3.0: Results

3.1: Respondents' Perception on Training Factors

Table 3.1 below presents respondents' perceptions of training factors among CHPs in Nyandarua County.

Item	SD (%)	D (%)	N (%)	A (%)	SA (%)	*n*	*Mean*	*SD*
Received CHP training before starting CHP work	0.9	5.7	1.3	42.3	49.8	320	4.34	0.84
Have another course apart from the CHP training	9.3	18.6	5.1	38.3	28.6	320	3.58	1.32
Always have ready internet for Learning	26.3	26.9	5.8	27.9	13.1	320	2.75	1.44
Get health learning materials	14.6	26.0	11.0	33.4	14.9	320	3.08	1.33
Often invited for health meetings to help you learn	5.0	13.6	6.9	54.6	19.9	320	3.71	1.09
CHP training venue was good for learning	0.9	9.1	11.4	47.6	30.9	320	3.98	0.94
Time lessons took for CHP training was enough	9.4	29.6	13.0	34.2	13.7	320	3.13	1.25
Training language was simply understandable	0.9	3.8	4.1	51.6	39.6	320	4.25	0.78
Liked appearance of CHPs trainers	1.6	1.9	2.5	48.7	45.3	320	4.34	0.76
Trainers understood topics well	1.6	2.6	6.1	47.9	41.9	320	4.26	0.81
Overall Average							**3.75**	**0.54**

Note: *SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree, n = sample size; M = Mean; SD = Standard Deviation*.

Respondents strongly agreed (mean= 4.34) that they received CHP training before starting work and positively rated trainers' competence, appearance and communication, with high mean scores (≈4.25–4.34). They also agreed that the training venue and additional learning opportunities were supportive (means 3.71–3.98). They also agreed moderately (mean 3.58) that they had received other training beyond CHP entry training.Neutral responses (means 2.75–3.13) were recorded regarding adequacy of learning materials, training duration and internet access, indicating gaps in learning resources and digital access.Overall, training factors were positively rated (mean = 3.75).

3.2: Model Summary of Training Factors on Knowledge Retention

Table 3.1: *Model Summary of Training Factors on Knowledge Retention*

Model	R	R^2	Adjusted R^2	Std. Error of Estimate	Change Statistics: R^2 Change	F Change	df1	df2	Sig. F Change
1	.163[a]	.027	.024	18.140	.027	8.693	1	317	.003

a. Predictors: (Constant), Training factors

The findings indicated a weak positive relationship between training factors and knowledge retention among CHPs, with a correlation coefficient (R = 0.163). The coefficient of determination (R^2 = 0.027) shows that training factors explain only 2.7% of the variation in knowledge retention, while the adjusted R^2 (0.024) confirms that this explanatory power remains low after model adjustment. Overall, training factors contributed a weak but positive influence on knowledge retention.

3.3:ANOVA Results of Training Factors on Knowledge Retention

Table 3.3: *ANOVA Results of Training Factors on Knowledge Retention*

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2860.625	1	2860.625	8.693	.003[b]
	Residual	104312.372	317	329.061		
	Total	107172.997	318			

a. Dependent Variable: Score
b. Predictors: (Constant), Training factors

The ANOVA results showed that the regression model was statistically but modestly significant, $F(1, 317) = 8.693$, $p = .003$, indicating that training factors significantlybut weakly predicted knowledge retention among CHPs. Overall, training-related aspects such as training delivery, refresher meetings, training language, learning environment, trainers' competence and learning materials were significant contributors to knowledge retention among CHPs.

3.4:Regression Coefficients of Training Factors on Knowledge Retention

Table 3.2: *Regression Coefficients of Training Factors on Knowledge Retention*

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	7.496	7.179		1.044	.297
	Training factors	5.590	1.896	.163	2.948	.003

a. Dependent Variable: Score

The regression results showed that training factors have a modestly significant positive effect on knowledge retention among CHPs. A unit increase in training factors led to a 5.590unit increase in knowledge retention ($\beta = 5.590$, $p = .003$), indicating a direct but a modest statistically significant relationship. The constant value (7.496) suggests that baseline knowledge retention existed even without training factors, though at a lower level. Overall, improvements in training-related factors significantly but modestlywould enhance knowledge retention among CHPs.

3.5: Respondents' Perception on Individual Factors

Table 3.5 below presents respondents' perceptions of individual factors among CHPs in Nyandarua County.

Item	SD (%)	D (%)	N (%)	A (%)	SA (%)	*n*	*M*	*SD*
Expectations met	9.6	21.8	28.8	25.0	14.7	320	*3.13*	1.20
Always available	1.6	1.6	1.6	40.8	54.4	320	*4.45*	0.75
Family acceptance	2.6	4.5	4.5	47.6	40.8	320	*4.20*	0.91
Community acceptance	1.9	0.9	6.6	47.2	43.4	320	*4.29*	0.79
Feel good about work	1.3	0.6	1.6	44.0	52.5	320	*4.46*	0.69
Personal work not lowering CHP work	3.3	5.3	10.6	52.5	28.4	320	*3.97*	0.95
Personal health not lowering CHP work	8.3	8.0	8.6	40.1	35.0	320	*3.86*	1.22
Overall Average							*4.06*	0.53

Note: *SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree, n = sample size; M = Mean; SD = Standard Deviation.*

Respondents were neutral regarding whether their expectations as CHPs had been met (mean = 3.13), indicating mixed perceptions. However, they generally agreed that family support, personal commitments and personal health did not hinder their CHP responsibilities. They also strongly agreed that the community was supportive (mean=4.29) and that CHPs felt positive(mean=4.46) about their CHP work. Overall, individual factors were positively rated (mean = 4.06 ± 0.53), suggesting that family support, positive attitudes, and community acceptance contributed favorably to CHP engagement.

3.6: Model Summary of the Effect of Individual Factors on Knowledge Retention

Table 3.6: *Model Summary of the Effect of Individual Factors on Knowledge Retention*[a]

Model	R	R^2	Adjusted R^2	Std. Error of Estimate	R^2 Change	F Change	df1	df2	Sig. F Change
1	.077[a]	.006	.003	.491	.006	1.905	1	318	.168

a. Predictors: (Constant), Individual factors
b. Dependent Variable: Score in the test

The findings indicated a very weak positive relationship between individual factors and knowledge retention among CHPs, with a correlation coefficient, R = 0.077. The coefficient of determination (R^2 = 0.006) showed that individual factors explained only 0.6% of the variation in knowledge retention, while the adjusted R^2 (0.003) confirms an even lower explanatory power after adjustment. Overall, individual factors contributed minimally to knowledge retention among CHPs.

3.7:ANOVA of the Effect of Individual Factors on Knowledge Retention

Table 3.7: *ANOVA of the Effect of Individual Factors on Knowledge Retention*[a]

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	.458	1	.458	1.905	.168[b]
Residual	76.514	318	.241		
Total	76.972	319			

a. Dependent Variable: Score in the test
b. Predictors: (Constant), Individual factors

The ANOVA results showed that the regression model was not statistically significant, F (1, 318) = 1.905, p = .168 (> .05), indicating that individual factors did not significantly predict knowledge retention among CHPs. Overall, the model was not useful in explaining variations in knowledge retention among CHPs.

3.8: Coefficients of the Effect of Individual Factors on Knowledge Retention

Table 3.8: *Coefficients of the Effect of Individual Factors on Knowledge Retention*[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.921	.211		4.367	.000
	Individual factors	.071	.051	.077	1.380	.168

a. Dependent Variable: Score in the test

The regression results indicated a positive but statistically non-significant relationship between individual factors and knowledge retention among CHPs (β = 0.071, p = .168). Although improvements in individual factors were associated with slight increases in knowledge retention, the effect was not statistically significant, suggesting that individual factors were not meaningful predictors of knowledge retention. This implies that other factors may have played a greater role in influencing knowledge retention among CHPs.

4.0: Discussion

This study examined the influence of training and individual factors on knowledge retention among CHPs in Nyandarua County, Kenya. The findings indicated that training factors were associated with knowledge retention, whereas individual factors showed no significant influence. These results suggest that the sustainability of learning among CHPs is shaped more by the quality of training than by individual factors.

The significant influence of training factors highlights the importance of training design in supporting long-term retention of knowledge among frontline health workers. Effective training extends beyond initial knowledge acquisition and requires instructional approaches that facilitate comprehension, memory consolidation and continued application of learning. These findings are consistent with studies demonstrating that learner-centered pedagogies, structured content delivery and opportunities for active engagement contribute to improved retention and performance among healthcare workers (Rogers et al., 2023; Wanjohi et al., 2022). Similarly, George et al. (2024) and Carpenter et al. (2022) emphasized that interactive learning approaches and reinforcement strategies enhance long-term retention by promoting retrieval practice and reducing knowledge decay.

The descriptive findings provide further insight into the mechanisms through which training may influence retention. Respondents generally reported positive perceptions of trainers' competence, communication and the training environment, suggesting that instructional quality was a strength of the CHP training program. However, relatively lower ratings for internet access, learning materials, and adequacy of training duration point to potential weaknesses in learning reinforcement. Previous research indicates that access to learning resources and continuous opportunities for practice are essential for maintaining competencies after training (Elias et al., 2024; Sacks et al., 2020). Without reinforcement, knowledge gained during initial training is likely to decline over time, consistent with established evidence on the forgetting curve and memory decay (Murre&Dros, 2025).

Although training factors were significant predictors, their overall explanatory contribution was relatively small. This suggests that knowledge retention is influenced by a broader set of determinants beyond the training characteristics examined in this study. Community health workers often operate within complex environments characterized by workload pressures, limited resources, competing responsibilities and varying levels of supervision. Such contextual factors may affect opportunities for knowledge application and reinforcement, thereby influencing retention outcomes (Tsofa et al., 2017; Wanjohi et al., 2022). Consequently, improving training quality alone may not be sufficient to optimize long-term competency unless accompanied by supportive organizational and system-level interventions.

In contrast, individual factors did not demonstrate a significant influence on knowledge retention. Although respondents generally reported positive attitudes toward their work, family support and community acceptance, these attributes were not associated with measurable differences in retained knowledge. This finding suggests that favorable personal and social circumstances may support participation and engagement in community health activities but may not necessarily translate into improved cognitive acquisition or retention of training content. Similar observations have been reported in resource-constrained settings where structural and environmental conditions exert a stronger influence on performance than individual characteristics (Kavle et al., 2019; Sacks et al., 2020).

These findings are consistent with Baldwin and Ford's Transfer of Training Model, which emphasizes that training outcomes depend on the interaction of training design, trainee characteristics and environmental factors. The current study provides evidence that training design appears to be more influential than trainee characteristics in determining retained knowledge among CHPs. This supports the view that knowledge retention is not solely an individual cognitive process but is strongly shaped by instructional quality and opportunities for post-training reinforcement (Sweller et al., 2019; Rogers et al., 2023). Therefore, even highly motivated individuals may experience knowledge decline when learning is not supported through refresher training, mentorship and continuous professional development.

An additional consideration was the variation in the year of entry training among CHPs. Since participants received their initial training at different periods following the introduction of Kenya's Community Health Strategy in 2006, they may have been exposed to different curricula, instructional methods and support systems. Changes in training content and implementation over time may have contributed to variation in retention outcomes that was not fully captured in the present analysis. Future studies should therefore examine cohort effects and the influence of training recency on knowledge retention.

Several limitations should be considered when interpreting these findings. First, the cross-sectional design limits the ability to establish causal relationships or directly assess changes in knowledge over time. Second, the use of self-administered questionnaires may have introduced response bias, while the knowledge assessment captured retention at a single point rather than longitudinally. Third, the study was confined to in-service CHPs in Nyandarua County, limiting the generalizability of findings to other settings which are not similar. Finally, the low explanatory power of the models suggests that additional factors, which may include supervision quality, organizational support, workplace learning opportunities and broader health system characteristics, may play a substantial role in determining knowledge retention.

Despite these limitations, the study contributes important evidence on factors associated with knowledge retention among Community Health Promoters in Kenya. The findings underscore the importance of strengthening training quality through learner-centered approaches, adequate learning resources, refresher training, mentorship and continuous professional development. Future research should adopt longitudinal designs and incorporate organizational, contextual and cohort-related variables to develop a more comprehensive understanding of the determinants of sustained learning and knowledge retention among CHPs.

5.0: Conclusion

This study concluded that training factors play a statistically but modestly significant role in determining knowledge retention among CHPs in Nyandarua County, while individual factors did not significantly influence retention outcomes. Although training-related variables such as trainer competence, training structure, learning environment and reinforcement mechanisms positively influenced knowledge retention, their overall explanatory power remained low, indicating that knowledge retention is likely shaped by broader contextual, organizational and system-level factors beyond training alone.

In contrast, individual characteristics such as education level, motivation, and prior experience showed no statistically significant effect on knowledge retention, suggesting that structural and instructional conditions of training are more influential than personal attributes in determining learning outcomes in this setting.

The relatively low explanatory power of the models may be attributed to the complexity of knowledge retention as an outcome, which is influenced by multiple interacting factors beyond those captured in the study, including workplace reinforcement, supervision quality and health system support. Additionally, variation in the year of training may have introduced cohort effects, as CHPs trained at different times were likely exposed to differing curricula, training methodologies and health system priorities, which may have influenced retention levels.

From a policy perspective, the findings underscore the need to shift from isolated, one-off training models toward structured continuous learning systems that incorporate refresher training, mentorship, supportive supervision and strengthened learning resources. Training programs should be redesigned to emphasize sustained competency development rather than short-term knowledge acquisition.

Overall, the study highlights that improving knowledge retention among CHPs requires a system-wide approach that integrates high-quality training design with continuous reinforcement mechanisms and supportive health system structures. Strengthening these elements is essential for ensuring sustained competency and improving the effectiveness of community health service delivery in resource-constrained settings.

Ethical Considerations

The study complied with Kenyatta University postgraduate ethical guidelines and obtained approval from the National Commission for Science, Technology and Innovation (NACOSTI/*Ref. No, 728874*). Additional permissions were obtained from the Nyandarua County Department of Health Services, the County Commissioner's Office and the County Director of Education. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection.

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