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Foreword

It is with great pleasure that I present Volume 7 of the *African Journal of Science, Technology and Engineering*. This volume marks another significant step forward in our mission to foster innovative research and knowledge dissemination across the African continent and beyond.

This edition features a rich collection of peer-reviewed articles addressing current and emerging issues in various fields ranging from emerging technologies, sustainable infrastructure, and advanced materials, to data-driven innovations and engineering applications tailored to local and global needs. The diversity and depth of contributions reflect the growing capacity and commitment of African scholars and practitioners in addressing complex scientific and technological challenges through locally relevant and globally informed solutions.

As Africa continues to assert its place in the global knowledge economy, it is vital that platforms like this journal provide visibility and support for homegrown research and innovations. Volume 7 not only celebrates intellectual achievement but also encourages collaboration, cross-disciplinary engagement, and practical application of science and technology to improve lives.

I commend the authors, reviewers, editorial board, and supporting institutions whose dedication and scholarly rigor have made realization of this volume possible. May this edition inspire further inquiry, innovation, and impactful solutions throughout Africa and the global scientific community.

Chief Editor

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KANGAROO MOTHER CARE: A STUDY OF OPPORTUNITIES AND CHALLENGES IN ITS IMPLEMENTATION AMONG MOTHERS OF PRETERM AND LOW BIRTH WEIGHT INFANTS IN KIRINYAGA COUNTY, KENYA

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ABSTRACT

Kangaroo Mother Care (KMC) is an essential newborn package for reduction of neonatal mortality rates among preterm and low birth weight babies. However, KMC uptake remains low in Kenya. This paper assessed the determinants of KMC utilization among mothers' post-hospitalization in Kirinyaga County, Central Kenya. A total of 152 KMC practicing mothers were enrolled in the study after discharge from Kerugoya County Hospital. The study adopted a descriptive and analytical cross-sectional design using both qualitative and quantitative methods. Structured questionnaires, key informant interviews, and focus group discussions were used to collect data. A systematic sampling method was adopted for recruitment of study participants. Chi-square was applied to test association between KMC predictors and their relationship with KMC uptake post-hospital discharge in Kirinyaga County. Of the 152 KMC-practicing mothers' included in the study were practicing KMC for ≥8 hours a day as recommended. Two demographic determinants (age and level of education) and two family support determinants (emotional/physical support and assistance to position) were associated with KMC uptake (p-value < 0.05) in this study. However, stigma, traditional beliefs, and cultural norms were identified as hindering the KMC practice among mothers' post-hospital discharge. Health system factors were also observed to have a moderating effect on determinants of KMC utilization. Results of this study demonstrate low KMC utilization in Kirinyaga County and highlights demographic, family support systems, sociocultural factors, and healthcare system factors as key determinants of KMC uptake.

Keywords: Kangaroo Mother Care, Utilization, Determinants, Post-Hospitalization, Kenya.

Key Messages

- Kangaroo Mother Care is a tried and tested method for promoting the survival of preterm and low-birth-weight infants. Despite efforts to promote KMC utilization among mothers' post-hospitalization, the uptake remains low.
- The study found demographic and family support determinants are associated with KMC uptake, but stigma, traditional beliefs, and cultural norms hindered practice among post-hospital discharge mothers, with health system factors moderating utilization.
- Interventions targeting community education and awareness, along with culturally sensitive approaches, may help address these barriers and increase KMC uptake among mothers.
- Additionally, strengthening health systems to provide ongoing support and resources for KMC implementation could further promote the intervention's adoption.

Introduction

Prematurity refers to babies born before 37 weeks' gestation, while low birth weight (LBW) refers to babies born weighing less than 2500 grams. Prematurity, along with low birth weight, directly contributes to neonatal mortality, making them significant risk factors for neonatal deaths. Currently, the majority of neonatal deaths are caused by being born prematurely, small for gestational age (SGA), or with a low birth weight[1]. Preterm births not only increase the risk of neonatal mortality and morbidity but also have long-term effects on physical health, such as developmental delays, neurodevelopmental disorders, and long-term financial implications because of ongoing medical needs[2].

The World Health Organization recommends Kangaroo Mother Care (KMC) as a high-impact, low-cost, effective intervention for promoting survival and development in resource-limited settings[3]. A review of 31 trials comparing KMC with conventional care found that it reduces mortality risks during birth and possibly reduces severe infection until the latest follow-up[4]. The reduction in mortality rate was greater when KMC was initiated within 24 hours after the baby was born. Kangaroo Mother Care reduces sepsis in premature infants, promotes calmness, bonding, and stress reduction, and improves health outcomes, while also empowering mothers, promoting exclusive breastfeeding, and reducing postpartum depression[2,5]. Notably, a recent Cochrane review revealed that neonates who received KMC had a 40% reduction in mortality, 72% reduction in hypothermia, and 65% reduction in severe infections when compared to standard care. KMC has also been reported to be affordable and reliable[6].

Similar to any intervention, Kangaroo Mother Care (KMC) faces its own set of challenges. The utilization of KMC varies from 11.04% to 84.36%. Benin, Tajikistan, and Uganda have the highest rates, and Burundi, Bangladesh, and Pakistan have the lowest rates. Low uptake has been observed in most countries within Sub-Saharan Africa[7]. KMC has a low uptake rate in Kenya, standing at 59%[8]. Nevertheless, there is insufficient data on the extent of Kangaroo Mother Care (KMC) coverage in Kirinyaga County. Kenya's Ministry of Health formulated an official

guideline for kangaroo mother care in 2015 and launched it in 2016 [9]. Later, KMC guidelines were revised in 2023 to upscale KMC uptake and reduce neonatal mortality rates[8].

Despite the progress made in understanding KMC within healthcare facilities, continuity of KMC post-discharge in resource-limited settings such as Kenya remains unknown. This study therefore focuses on exploring and understanding the challenges, facilitators and barriers to implementation of KMC continuity at home post-hospital discharge within communities in Kirinyaga County, Kenya.
The cross-sectional study has been reported in line with the STROBES guidelines.

Materials and Methods

Study Design

A total of 152 mothers were enrolled in the study after discharge from Kerugoya County Referral Hospital in Kenya. The study used a cross-sectional design using quantitative and qualitative data. The chi-square test for association was used to examine association between demographic determinants, family support system determinants, and health system factors and utilization of KMC at home.

Location of the Study

The study was carried out in Kirinyaga County which is located in the Central region of Kenya approximately 107 kilometers northeast of Nairobi (Figure 1). Kirinyaga County has 109 public hospitals, consisting of 51 level one facilities, 45 level two facilities, 10 level three facilities, 3 level four facilities, and one level five facility (Kerugoya County Referral Hospital, KCRH). KCRH was selected for this study because it is the referral hospital for Kirinyaga County which has ultra-modern infrastructures and relatively adequate staffing level. The facility is a point of call to all patients referred from lower-level hospitals in Kirinyaga County for critical and specialized treatment thus reflecting a true representation of the population of Kirinyaga County. KCRH also serves neighboring counties of Embu, Nyeri and Murang'a thus representing a large socio-cultural diverse population which is ideal for study and generalization.

Sample Size and Sampling Technique

The study population comprised a total of 250 postnatal mothers of preterm infants and low-birth-weight infants attending the postnatal clinic. Fischer et al.'s (1991) formula was used to calculate the sample size.

$nf = \frac{n}{(1+{}^{n}/_{N})}$

Where:

nf→ *sample adjustment*

n→ *Sample size.*

N→ *Population of the study* → (*250 attendants of neonatal clinic*)

$$nf \rightarrow \frac{384}{1+{}^{384}/_{250}} = \underline{\textbf{152 participants}}$$

A total of 152 participants were selected for the study. The inclusion criteria were KMC mothers of preterm/LBW babies with a minimum age of 18 years. KMC mothers with sick babies and multigravidae were excluded from the study. Participants were selected using a systematic sampling method. The clinic attendance register was used as a sampling frame. A sampling interval of two was adopted to identify study participants, which was obtained by dividing 250 by 152. Study participants were selected by identifying the first name of a study participant in the hospital attendance register. The second participant was identified by skipping the second and third names in the hospital clinic attendance register. This sampling procedure was repeated until the sample size of 152 participants was obtained.

Data Sources and Collection Tools

Data collection was undertaken using a structured questionnaire, an interview guide for the key informant interview and a focus group discussion guide for the focused group discussions.

Sources of Bias

To guarantee that data collection was appropriate for this study, the validity of the study instrument was assessed using content validity and construct validity. Content validity was assessed to check whether sampled specific domain indicators in the questionnaire accurately represent concepts under the study and assess what concept the instrument is attempting to measure. Construct validity was assessed using factor analysis to determine whether the instrument accurately measures the theoretical constructs it is intended to measure. Sources of bias or confounding variables were explored and addressed to improve the overall validity of the study. The instrument was evaluated for reliability to ensure consistent results when used multiple times. Test-retest reliability was used to determine stability over time

Data Collection Procedure

Structured questionnaires were administered to study participants. Two focus group discussions, each comprising 6 participants, were held. Participants with preterm babies and/or LBW babies were included in the focus group. The duration of the FDGs was 90 minutes. During the FGDs, study observations were recorded using tape, video recording, and note-taking. Qualitative data was also collected using KII with one (1) pediatric clinical officer and one (1) nurse.

Patient and Public involvement

The study population included mothers of preterm and low-birth-weight infants attending the postnatal clinic and two healthcare workers in the postnatal clinic. A formative exploratory phase involved clinical interviews and focus group discussions with mothers discharged from

the KCRH postnatal ward. A pilot study with a small cohort was further carried out to assess the feasibility of study materials and refine the data collection procedures. Results of this study are meant to inform future interventions and programs aimed at supporting mothers of preterm and low-birth-weight infants in the community.

Operational Definition of Variables

Demographic factors are defined as age, level of education, marital status, number of children, employment status and level of income.
The family support system is defined as physical and emotional support to the mother.
Socio-cultural factors are defined as community exposure, cultural attitudes and traditional beliefs as well as misconceptions about KMC.
Health system factors are defined as standardized protocols, attitude of health workers and access to healthcare services.
Utilization of KMC is defined as practicing KMC for more than 8 hours a day.

Data Analysis

Quantitative data was coded, cleaned and entered into an Excel sheet before analysis. The research questions and interview guide were used to create a coding frame. Analysis was done using SPSS version 20. Pearson coefficient of correlation and chi-square test for association were used to test for association between variables. A multiple linear regression model was used to determine the extent to which demographic factors, family support system, sociocultural factors and health system factors influence utilization of KMC. Data was presented in the form of tables. Qualitative data was transcribed and entered into a Word document. The research questions and study objectives were used to create a coding frame. Inductive thematic analysis was done using NVIVO version 12. Data was presented in themes.

Results

Demographic Characteristics of Participants

The demographic characteristics examined in the study included age, level of education, marital status, number of children, and monthly income of the respondents (Table 1).

Table 1: Demographic Characteristics of Participants

Demographic Factors (n = 152)	n (%)
Age band in years	
18-25	45 (29.6)
26-30	36 (23.7)
31-35	48 (31.6)
36-40	7 (4.6)

Demographic Factors (n = 152)	n (%)
>40	16 (10.5)
Level of Education	
Tertiary	61 (40.1)
Secondary school	54 (35.5)
Primary school	33 (21.7)
Never been to school	4 (2.6)
Marital Status	
Married	91 (59.9)
Single	43 (28.3)
Divorced/Separated	10 (6.6)
Widowed	4 (2.6)
Total	148 (97.4)
Missing	4 (2.6)
Parity (Number of children)	
Missing	4 (2.6)
1	50 (32.9)
2	42 (27.6)
3	32 (21.1)
4	21 (13.8)
5	3 (2)
Employment Status	
Unemployed	57 (37.5)
Self-employed	57 (37.5)
Employed	38 (25)
Level of income (income per month in Kenyan shillings)	
Less than 10000	40 (26.3)
10000-20000	30 (19.7)
20001-50000	40 (26.3)
Above 50000	17 (11.2)
Missing	25 (16.4)

Note. Missing represents number of participants who left the question item unanswered question in the questionnaire.

Level of KMC Utilization among Mothers Post Hospitalization

18 of 152 11.8% of participants practiced KMC post-hospitalization at KCRH for at least 8 hours (Table 2). The rest of participants practice KMC intermittently, the duration ranged from less than 3 hours to 8 hours and above.

Table 2: Level of Utilization

Utilization of KMC (n=152)	Frequency	Percent %
Continuity of kangaroo mother care at home		
Yes	140	92.10%
No	12	7.90%
Total	152	100.00%
Duration of KMC practice at home		
<3 hours	67	44.10%
3-7 hours	55	36.20%
≥8 hours	18	11.80%
Total	140	92.10%

A total of 140 out of 152 participants were used to analyze association between the predictor variables and Kangaroo Mother Care utilization among mothers' post-hospitalization. The remaining 12 participants were excluded from the analysis because they had discontinued the practice of KMC at home. The participants were further categorized based on the duration they practiced KMC (i.e., < 3 hours, 3–7 hours, and ≥ 8 hours). The chi-square test for independence was used to determine association between each predictor variable and the outcome variable. The level of significance was set at a p-value of < 0.05.

Demographic Determinants of KMC Utilization among Mothers Post Hospitalization

The demographic characteristics examined in the study included age, level of education, marital status, number of children, and monthly income of the respondents. This study revealed that employment status was the only demographic determinant that was significantly associated (p-value = 0.024) (Table 3).

Table 3: Association between Demographic Determinants and Utilization of KMC Among Mothers Post Hospitalization

Demographic determinants of KMC n = 140	Number of participants practicing KMC for different duration in hours (%)			Total	χ^2	P value
	<3	3 – 7	≥ 8			
Age category						
18-25	16 (23.9%)	12 (21.8%)	8 (44.4%)	36 (25.7%)		
26-30	20 (29.9%)	12 (21.8%)	4 (22.2%)	36 (25.7%)		
31-35	15 (22.4%)	24 (43.6%)	6 (33.3%)	45 (32.1%)	13.012	0.089[a]
36-40	4 (6.0%)	3 (5.5%)	0 (0.0%)	7 (5.0%)		
>40	12 (17.9%)	4 (7.3%)	0 (0.0%)	16 (11.4%)		
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		
Level of education						
Tertiary	31 (46.3%)	20 (36.4%)	7 (38.9%)	58 (41.4%)		
Secondary school	28 (41.8%)	19 (34.5%)	6 (33.3%)	53 (37.9%)	6.264	0.177[a]
Primary school	8 (11.9%)	16 (29.1%)	5 (27.8%)	29 (20.7%)		
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		
Marital status						
Married	47 (70.1%)	29 (56.9%)	15 (83.3%)	91 (66.9%)		
Single	16 (23.9%)	12 (23.5%)	3 (16.7%)	31 (22.8%)		
Divorced/ Separated	4 (6.0%)	6 (11.8%)	0 (0.0%)	10 (7.4%)	9.188	0.120[a]
Widowed	0 (0.0%)	4 (7.8%)	0 (0.0%)	4 (2.9 %)		
Total	67 (49.3%)	51 (37.5%)	18 (13.2%)	136 (100 %)		
Number of children						
Missing	4 (6.0%)	0 (0.0%)	0 (0.0%)	4 (2.9%)		
1	20 (29.9%)	18 (32.7%)	4 (22.2%)	42 (30.0%)		
2	19 (28.4%)	14 (25.5%)	5 (27.8%)	38 (27.1%)		
3	16 (23.9%)	7 (12.7%)	9 (50.0%)	32 (22.9%)	2.097	0.350[b]
4	8 (11.9%)	13 (23.6%)	0 (0.0%)	21 (15.0%)		
5	0 (0.0%)	3 (5.5%)	0 (0.0%)	3 (2.1%)		
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		
Employment status						
Unemployed	20 (29.9%)	23 (41.8%)	5 (27.8%)	48 (34.3%)	11.106	0.024[a]

Demographic determinants of KMC n = 140	Number of participants practicing KMC for different duration in hours (%)			Total	χ^2	P value
	<3	3 – 7	≥ 8			
Self Employed	28 (41.8%)	23 (41.8%)	3 (16.7%)	54 (38.6%)		
Employed	19 (28.4%)	9 (16.4%)	10 (55.6%)	38 (27.1%)		
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		
Monthly income (Ksh)						
Less than 10000	12 (25.5%)	19 (37.3%)	5 (27.8%)	36 (31.0%)		
10000-20000	8 (17.0%)	15 (29.4%)	3 (16.7%)	26 (22.4%)		
20001-50000	19 (40.4%)	12 (23.5%)	6 (33.3%)	37 (31.9%)	7.023	0.314[a]
Above 50000	8 (17.0%)	5 (9.8%)	4 (22.2%)	17 (14.7%)		
Total	47 (40.5%)	51 (44.0%)	18 (15.5%)	116 (100.0%)		

Note. [a] Statistical significance was determined using chi square. [b] Statistical significance was determined using Kruskal Wallis test.
Note. Variations in the total number of responses across parameters are due to non-response on specific questionnaire items, in addition to cases excluded because they discontinued with KMC at home (n = 12).
Note. The total percentages in this table were calculated using the total study population (N = 140) as the denominator for each cell, rather than using the total number of responses per row or column.

Family Support System Determinants and KMC Utilization Among Mothers Post Hospitalization

127of 140 (90.7%) mothers received family support to position the baby for KMC; 80 of 140 (57.9%) received support in taking care of the baby, while 22 of 140 (15.7%) received support in taking care of household duties such as cooking 109 of 140 (77.9%). Only 15.7% of mothers practicing KMC post-hospitalization received a negative perception of practicing KMC from family and friends. Support with taking care of the baby and household duties, positive perception of family and friends, and active family members' participation in KMC were significantly associated (p-value < 0.05) with KMC utilization post-hospitalization. (Table 4).

Table 4: Association between Family Support Determinants and Utilization of KMC Among Mothers Post Hospitalization

Family support determinants n = 140	Number of participants practicing KMC for different duration in hours (%) < 3	3 – 7	≥8	Total	χ^2	*P* value
Emotional encouragement and hands on practical assistance in positioning the baby in KMC position.						
Yes	63 (94.0%)	46 (83.6%)	18 (100.0%)	127 (90.7%)		
No	4 (6.0%)	9 (16.4%)	0 (0.0%)	13 (9.3%)	5.988	0.058
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		
Negative perception from family or friends about practicing KMC						
Yes	8 (11.9%)	14 (25.5%)	0 (0.0%)	22 (15.7%)		
No	59 (88.1%)	41 (74.5%)	18 (100.0%)	118 (84.3%)	8.016	0.017
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		
Spousal assistance with baby care task (e.g. diaper change)						
Yes	39 (58.2%)	27 (49.1%)	13 (72.2%)	79 (56.4%)		
No	28 (41.8%)	28 (50.9%)	5 (27.8%)	61 (43.6%)		
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)	3.117	0.210
Family support with household duties such as cooking						
Yes	63 (94.0%)	33 (60.0%)	13 (72.2%)	109 (77.9%)		
No	4 (6.0%)	22 (40.0%)	5 (27.8%)	31 (22.1%)	20.670	0.000
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		
Active family members participation in KMC and shared caregiving roles.						
Yes	31 (46.3%)	41 (74.5%)	9 (50.0%)	81 (57.9%)		
No	36 (53.7%)	14 (25.5%)	9 (50.0%)	59 (42.1%)	10.428	0.005
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		

Note. The total percentages in this table were calculated using the total study population (N = 140) as the denominator for each cell, rather than using the total number of responses per row or column.

Note. The total study population was 152. However, only 140 participants who reported to continue with KMC at home were used during the analysis. Variations in the total number of responses across parameters are due to non-response on specific questionnaire items, in addition to cases excluded because they discontinued with KMC at home (n = 12).

Health System Determinants of KMC Utilization Among Mothers Post Hospitalization.

It was observed that two health system factors were significantly associated with KMC uptake at KCRH post-hospitalization, namely training of mothers on KMC and post-discharge support and encouragement from healthcare workers on KMC (Table 5).

Table 5: Association between Health System Factors and Utilization of KMC Among Mothers Post Hospitalization

Health System Factor determinants	Number of Participants practicing KMC for different duration in hours (%)			Total	χ^2	P value
	< 3	3 – 7	≥8			
Receiving instructions on home based KMC						
Yes	60 (89.6%)	50 (90.9%)	15 (83.3%)	125 (89.3%)		
No	7 (10.4%)	5 (9.1%)	3 (16.7%)	15 (10.7%)	0.823	0.640
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		
Instructions given on home based KMC practice						
Cover the child with warm clothes while practicing KMC	48 (85.7%)	7(14.0%)	3 (16.7%)	58 (46.8%)		
Ensure skin to skin contact	8 (14.3%)	36 (72.0%)	11 (61.1%)	55 (44.4%)		
Adequate breastfeeding alongside practice of KMC	0 (0.0%)	7 (14.0%)	1 (5.6%)	8 (6.5%)	80.013	0.000
child will grow weak	0 (0.0%)	0 (0.0%)	3 (16.7%)	3 (2.4%)		
Total	56 (45.2%)	50 (40.3%)	18 (14.5%)	124 (100.0%)		
Perceived support and encouragement from healthcare workers on KMC post discharge						
Good	60 (89.6%)	34 (61.8%)	12 (66.7%)	106 (75.7%)		
Fair	7 (10.4%)	21 (38.2%)	6 (33.3%)	34 (24.3%)	13.555	0.001
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		
Engagement and listening by healthcare workers on concerns regarding KMC						
Yes	60 (89.6%)	41 (74.5%)	17 (94.4%)	118 (84.3%)		
No	7 (10.4%)	11 (20.0%)	1 (5.6%)	19 (13.6%)	8.705	0.083
I don't know	0 (0.0%)	3 (5.5%)	0 (0.0%)	3 (2.1%)		
Total	67 (47.9%)	55 (39.3%)	18 (12.9%)	140 (100.0%)		

Note. The total study population was 152. However, only 140 participants who reported to continue with KMC at home were used during the analysis. Variations in the total number of responses across parameters are due to non-response on specific questionnaire items, in addition to cases excluded because they discontinued with KMC at home (n = 12).

Discussion

This study revealed that employment status was the only demographic determinant that was significantly associated (*p-value* = 0.024) with KMC utilization among mothers post-hospitalization at KCRH, as reported elsewhere [10]. Unemployed mothers, as compared to those in formal employment, were 5.111 times more likely to practice KMC for 3 – 7 hours. Self-employed mothers were 4.912 times more likely to carry out for less than three (3) hours and 8.519 times more likely to carry out KMC for 3 – 7 hours as compared to employed mothers who carried out KMC for more than eight (8) hours. Hence, 55.6% of the mothers who practiced KMC for eight or more (≥8) hours were employed. These results suggest that employed mothers are more likely to practice KMC post-hospitalization at KCRH. This is plausibly due to guaranteed regular income and the availability of 90-day maternity leave in Kenya [11].

Support with taking care of the baby and household duties, positive perception of family and friends, and active family members' participation in KMC were significantly associated (p-value < 0.05) with KMC utilization post-hospitalization at KCRH. The likelihood of mothers who received family support with household duties in practicing KMC for 3 hours was 6.274. Specifically, for a one-unit increase in family support with household duties, log odds of practicing KMC for three (3) hours increases by 1.836. On the other hand, the likelihood of those who received support from family members in carrying the baby in KMC and shared caregiving roles practicing KMC for 3 – 7 hours was 3.628. Specifically, for a one-unit increase in active family members' participation in KMC and shared caregiving roles, the log odds of practicing KMC for 3 – 7 hours increased by 1.289. 41 of 55 (74.5%) of the mothers who practiced KMC did it for 3 – 7 hours. Previous studies have shown that physical and emotional support from family members, particularly spouses, significantly contributes to the uptake of childbirth management (KMC) [12,13, 14,15]. However, financial burdens, such as time spent in the hospital and lack of transport, also hinder KMC implementation. This highlights the importance of family support systems in promoting KMC adoption and overcoming challenges in implementing KMC.

Home-based KMC instructions and receiving support and encouragement from healthcare workers were significantly associated with KMC utilization in this study. Previous studies suggest that the strength of healthcare systems greatly affects the uptake of KMC. In particular, previous studies demonstrate that improved and adequate healthcare support promote the uptake of KMC [15–17].

Qualitative Data Findings and Interpretation

Qualitative data was gathered through key informant interviews and focus group discussions. Data was transcribed, coded and analyzed. Three major themes were identified which included: mothers' experiences, community perception, healthcare support system.

One KII stated, *"it is difficult to sustain follow-up care. A significant number of mothers are in remote areas and yet we have inadequate staffing to reach them. Additionally, the healthcare facilities in remote areas tend to be overburdened. They have limited resources such as counselling facilities as well as staff to offer individualized and personalized care to the mothers*." This perspective underscores inadequate health workers and distance from the hospital to the residence of mothers practicing KMC as plausible barriers to the utilization of KMC post-hospitalization in Kerugoya county.

Another barrier to KMC uptake was the lack of support groups for KMC, which are organized and run by healthcare workers, and a place to hold group discussions. This was exemplified by a comment by a healthcare worker who stated, *"we cannot give enough KMC follow-up as expected. Some of the mothers complain that they would like support group forums to share their experiences and learn from other mothers. Unfortunately, we do not have designated rooms for that. Some of the mothers are lost to follow up. We have inadequately trained healthcare staff at KMC to provide consistent follow-up at the community level".* Transition can be particularly challenging for mothers in rural areas who may face additional barriers in accessing healthcare services and support [18]. The findings are congruent with a study in China that reported insufficient health resources impede KMC practice. The study reported a low nurse-to-patient ratio hinders effective implementation of KMC [18].

Provision of unclear and conflicting information on KMC by healthcare workers was also observed in the study. For example, a mother practicing KMC stated that on one hand she was advised to, *"'do skin to skin contact' and ' continue with KMC until the baby is 3 kilograms'* whereas in another instance she was advised to *'keep the child warm when doing KMC', ' position the baby in KC position for one hour in a day', ' put the baby in KC position only when it is cold' ,'do skin to skin contact and continue with exclusive breastfeeding'".* Similar findings have been reported elsewhere. For instance, a study in China reported a lack of uniformity or standardization in the KMC standard operational procedure [18]. It is also worth noting that suboptimal monitoring of the outcome of KMC in this study was manifested in this study. This is shown by the contextualization of KMC outcomes with statements such as "*my baby is fat", "my baby is thin", "my baby is big","my baby is small"* to assess growth and monitoring of the preterm babies/LBW. This is in contrast with a study conducted in Pakistan that reported the existence of protocols to monitor and encourage the practice of KMC [19]. The discrepancy in the findings could be explained by the research design. Thus, the study carried out in Pakistan adopted a mixed-method approach involving a formative research phase and an interventional phase. Whereas this study adopted a purely analytical cross-sectional design.

Conclusion

Demographic factors such as employment, family support such as emotional and physical support, health system factors, specifically home-based instructions on how to continue with KMC at home, and perceived support and encouragement of KMC mothers by health care workers all influenced KMC utilization.

Limitations of the Study

The study employed a descriptive and analytical cross-sectional study designs that has the potential for overgeneralization. This study employed methodological triangulation by making use of both qualitative and quantitative research methodologies to provide a comprehensive analysis by combining qualitative and quantitative data giving a more holistic view of the determinants of this intervention.

Acknowledgement Statement

- *Assistance with the study*: none
- *Presentation*: none

Data Sharing statement

All data relevant to the study has been included in the article or uploaded as supplementary information.

Ethical Statement

This study involves human participants and was approved by the Mount Kenya University Ethics Review Committee and the National Commission for Science, Technology and Innovation.

- National Commission for Science, Technology and Innovation - NACOSTI/P/25/414906
- Mount Kenya Institution Ethics Review Committee – MKU/ISERC/4612

Additionally, authorization was sought from the county research officer and hospital administrator. Informed consent was obtained from the study participants in written form.

References

1. Ashorn P, Ashorn U, Muthiani Y, et al. Small vulnerable newborns-big potential for impact. *Lancet Lond Engl*. 2023;401(10389):1692-1706. doi:10.1016/S0140-6736(23)00354-9
2. Wang Y, Zhao T, Zhang Y, Li S, Cong X. Positive Effects of Kangaroo Mother Care on Long-Term Breastfeeding Rates, Growth, and Neurodevelopment in Preterm Infants. *Breastfeed Med*. 2021;16(4):282-291. doi:10.1089/bfm.2020.0358
3. Arya S, H N, K, et al. Immediate "Kangaroo Mother Care" and Survival of Infants with Low Birth Weight. *N Engl J Med*. 2021;384(21):2028-2038. doi:10.1056/NEJMOA2026486
4. Sivanandan S, Sankar MJ. Kangaroo mother care for preterm or low birth weight infants: a systematic review and meta-analysis. *BMJ Glob Health*. 2023;8(6): e010728. doi:10.1136/bmjgh-2022-010728
5. Cristóbal Cañadas D, Parrón Carreño T, Sánchez Borja C, Bonillo Perales A. Benefits of Kangaroo Mother Care on the Physiological Stress Parameters of Preterm Infants and Mothers in Neonatal Intensive Care. *Int J Environ Res Public Health*. 2022;19(12):7183. doi:10.3390/ijerph19127183

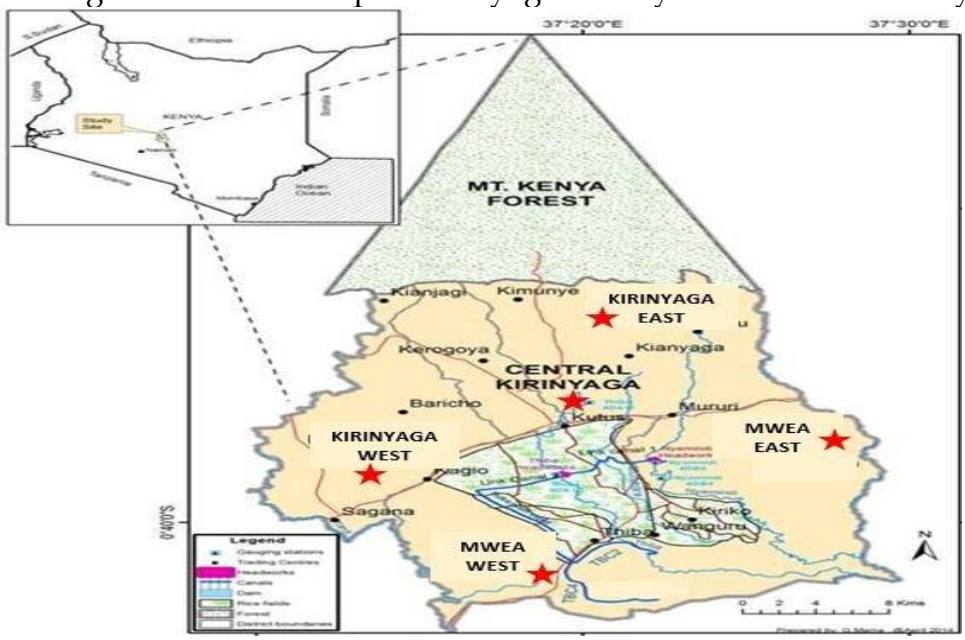
6. Adejuyigbe EA, Agyeman I, Anand P, et al. Evaluation of the impact of continuous Kangaroo Mother Care (KMC) initiated immediately after birth compared to KMC initiated after stabilization in newborns with birth weight 1.0 to < 1.8 kg on neurodevelopmental outcomes: Protocol for a follow-up study. *Trials*. 2023;24(1):265. doi:10.1186/s13063-023-07192-5
7. Lawal TV, Lawal DI, Adeleye OJ. Determinants of Kangaroo Mother Care among low-birth-weight infants in low resource settings. *PLOS Glob Public Health*. 2023;3(9):e0002015. doi:10.1371/journal.pgph.0002015
8. Murianki C, Irimu G, Musoke R, Maugo B. Prevalence, Facilitators of and Barriers To Kangaroo Mother Care Practice in the Newborn Unit At Kenyatta National Hospital. In: *Kenya Pediatric Organization*. ; 2018:1-5.
9. Ministry of Health. Kangaroo Mother Care: Clinical Implementation Guidelines 2016. Published online 2016:50.
10. Samsudin S, Chui PL, Kamar ABA, Abdullah KL. Maternal Kangaroo care education program in the neonatal intensive care unit improved mothers' perceptions, knowledge, perceived barriers and stress relates to premature infant. *Nurs Open*. 2023;10(1):349-357. doi:10.1002/nop2.1311
11. *Employment Act*.; 2019. Accessed May 12, 2025. https://new.kenyalaw.org/akn/ke/act/2007/11/eng%402019-11-25
12. Jamali QZ, Shah R, Shahid F, et al. Barriers and enablers for practicing kangaroo mother care (KMC) in rural Sindh, Pakistan. *PLoS ONE*. 2019;14(6):e0213225. doi:10.1371/journal.pone.0213225
13. Gidey S, Gebremariam DS, Hadush MY, et al. Practice of Kangaroo Mother Care Among Low-Birth-Weight Infants Discharged from Health Facilities and Its Outcome in Mekelle City, Tigray, Northern Ethiopia. *Int J Gen Med*. 2023;16:757-768. doi:10.2147/IJGM.S396471
14. Lydon M, Longwe M, Likomwa D, et al. Starting the conversation: community perspectives on preterm birth and kangaroo mother care in southern Malawi. *J Glob Health*. 2018;8(1):010703. doi:10.7189/jogh.08.010703
15. Bilal SM, Tadele H, Abebo TA, et al. Barriers for kangaroo mother care (KMC) acceptance, and practices in southern Ethiopia: a model for scaling up uptake and adherence using qualitative study. *BMC Pregnancy Childbirth*. 2021;21(1). doi:10.1186/s12884-020-03409-6
16. Lydon MM, Lwesha V, Likomwa D, Chimtembo L, Guenther T, Longwe M. Re-envisioning Kangaroo Mother Care Implementation Through a Socioecological Model: Lessons From Malawi. *Glob Health Sci Pract*. 2022;10(4):e2100727. doi:10.9745/GHSP-D-21-00727
17. Mathias CT, Mianda S, Ginindza TG. Facilitating factors and barriers to accessibility and utilization of kangaroo mother care service among parents of low birth weight infants in Mangochi District, Malawi: a qualitative study. *BMC Pediatr*. 2020;20(1). doi:10.1186/S12887-020-02251-1
18. Cai Q, Zhou Y, Hong M, Chen D, Xu X. Healthcare providers' perceptions and experiences of kangaroo mother care for preterm infants in four neonatal intensive care units in China: a qualitative descriptive study. *Front Public Health*. 2024;12:1419828. doi:10.3389/fpubh.2024.1419828

19. Muhammad S, Soomro A, Ahmed Khan S, et al. Scaling Up Kangaroo Mother Care Through a Facility Delivery Model in Rural Districts of Pakistan: Protocol for a Mixed Methods Study. *JMIR Res Protoc*. 2025;14:e56142. doi:10.2196/56142

Figure Legend

Figure 1: Map of Kirinyaga County

This figure shows the map of Kirinyaga County which was the study location.



ARTIFICIAL INTELLIGENCE ADOPTION AND USE IN ACADEMIC LIBRARIES IN KENYA: OPPORTUNITIES, CHALLENGES, READINESS FACTORS AND POLICY IMPLICATIONS

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ABSTRACT

Artificial Intelligence (AI) is transforming academic libraries by driving breakthroughs in information discovery, automation of library operations, enhancing research analytics, and personalized user services. This paper examines AI adoption and use in academic libraries in Kenya, focusing on current applications, opportunities, barriers, readiness factors, and overarching policy implications. This study adopted a Systematic Literature Review (SLR) approach guided by the Technology–Organization–Environment (TOE) Framework. Literature published between 2020 and 2025 was retrieved and synthesized from leading scholarly databases, professional reports, and policy documents. Findings indicate that AI presents robust opportunities for intelligent information retrieval, automated cataloguing, virtual reference services, research analytics, digital preservation, and advanced knowledge discovery. Notably, however, systemic adoption remains at an emerging stage due to inadequate ICT infrastructure, financial limitations, insufficient AI competencies among information professionals, ethical anxieties, resistance to organizational change and lack of formalized governance frameworks. We recommend strategic investment in digital infrastructure, development of institutional AI policies, continuous professional development initiatives, ethical governance mechanisms, and integration of AI competencies into modern Library and Information Science (LIS) education curricula.

Keywords: Artificial Intelligence, Academic Libraries, Digital Transformation, Technology Adoption, Research Support Services, Kenya, TOE Framework, AI Governance.

INTRODUCTION

Artificial Intelligence (AI) has emerged as a disruptive technological force, radically reshaping the paradigms of information management, knowledge curation, and institutional service delivery. Globally, academic libraries—long regarded as the intellectual hubs of higher education institutions—are exploring AI-driven technologies to maximize resource discovery, automate highly repetitive operations, empower researchers with predictive analytics, and deliver highly personalized information services.

AI applications within contemporary information spaces are multifaceted, spanning, intelligent information retrieval systems and semantic search engines, natural Language Processing (NLP) chatbots and virtual reference assistants, machine learning-based automated metadata generation and automated cataloguing, context-aware recommendation engines and predictive library analytics and AI-enabled research support tools and automated digital preservation pipelines.

These sophisticated systems allow contemporary libraries to pivot away from passive, transactional service delivery models toward proactive, intelligent, and user-centric knowledge environments.

In the Kenyan context, higher education institutions have achieved commendable milestones in foundational digital transformation in the past two decades. Thus, a number of universities have successfully institutionalized electronic resource management systems (ERMS), open-access institutional repositories (IRs), and advanced Integrated Library Systems (ILS). However, despite these foundational achievements, adoption of advanced, cognitive AI technologies remains conspicuously low or relegated to isolated pilot projects. The systemic gap between experimental interest and institutionalized deployment stems from a complex matrix of technological, organizational, financial, and regulatory challenges remains wide.

Thus, while AI applications present unprecedented opportunities to revolutionize academic library ecosystems and catalyze research support services, its structural adoption within Kenyan universities is visibly constrained. The current academic discourse in developing nations remains heavily skewed toward conceptual AI awareness, hypothetical use cases, and technological possibilities, leaving a notable empirical gap regarding practical institutional preparedness, ethical governance, long-term financial sustainability, and local policy frameworks.

Without targeted strategic interventions, academic libraries in Kenya risk experiencing fragmented and unequal technological adoption, inefficient or redundant IT infrastructure investments, compromised data privacy, and systemic biases. Consequently, there is therefore, an urgent need to systematically dissect the specific barriers, opportunities, and readiness metrics that govern how Kenyan library environments can ethically, efficiently, and sustainably assimilate AI into their operational fabrics. This study examines the structural landscape of AI

adoption within Kenyan academic libraries, deploying the Technology–Organization–Environment (TOE) framework to map out institutional readiness, technical capacities, and external environmental imperatives required for sustainable transformation.

OBJECTIVES

The primary objective of this study was to critically analyze the dynamics of AI adoption and use within academic libraries in Kenya. The specific objectives were to;

1. examine the current status and depth of AI adoption within Kenyan academic libraries.
2. identify the core opportunities presented by AI configurations in augmenting library services and institutional research output.
3. investigate the technical, operational, and structural challenges hampering systemic AI implementation.
4. analyze the technological, organizational, and environmental readiness factors of these institutions using the TOE Framework.
5. propose actionable policy recommendations and strategic interventions for sustainable, scalable, and ethical AI integration.

LITERATURE REVIEW

Defining AI in the Library Landscape

In the context of information science, AI refers to computational architectures capable of executing complex tasks traditionally requiring human cognitive faculties, such as machine learning, contextual reasoning, natural language comprehension, pattern recognition, and autonomous decision-making. In academic libraries, AI goes beyond standard automation (e.g., barcode scanning or basic SQL querying) by allowing systems to continuously learn from user data patterns, self-correct, and autonomously optimize workflow processes (Asemi and Asemi, 2023)[1].

Typology of Key AI Applications in Academic Libraries

AI DOMAIN	CORE APPLICATION	INSTITUTIONAL VALUE/IMPACT
Information Discovery	Intelligent Information Retrieval and Semantic Search	Moves past keyword matching to interpret user semantic intent, drastically reducing search fatigue (Breeding, 2024)[2].
User Services	Chatbots and virtual reference assistants	Provides 24/7 interactive support, answers FAQs, and assists users in navigating complex research databases (Lo, 2024)[3].

Technical Services	Automated cataloguing and metadata generation	Uses Computer Vision and NLP to auto-extract metadata, classify texts, and assign subject headings rapidly.
Collection Management	Recommendation systems and predictive analytics	Analyzes historic usage behavior to predict future resource demands, optimizing collection acquisition budgets.
Research Support	AI-Enabled analytics and citation mapping	Map research trends, automate systematic reviews, and evaluate institutional citation impacts (Cox et al., 2024)4.
Archival Science	Digital preservation and handwritten Text recognition	Automatically transcribes, indexes, and repairs metadata patterns within digitized historical manuscripts and institutional repositories.

Theoretical Underpinnings: The TOE Framework

To evaluate how complex innovations are integrated, this study relies on the **Technology–Organization–Environment (TOE) Framework** (Tornatzky and Fleischer, 1990)[5]. The framework splits adoption influences into three interconnected spheres:

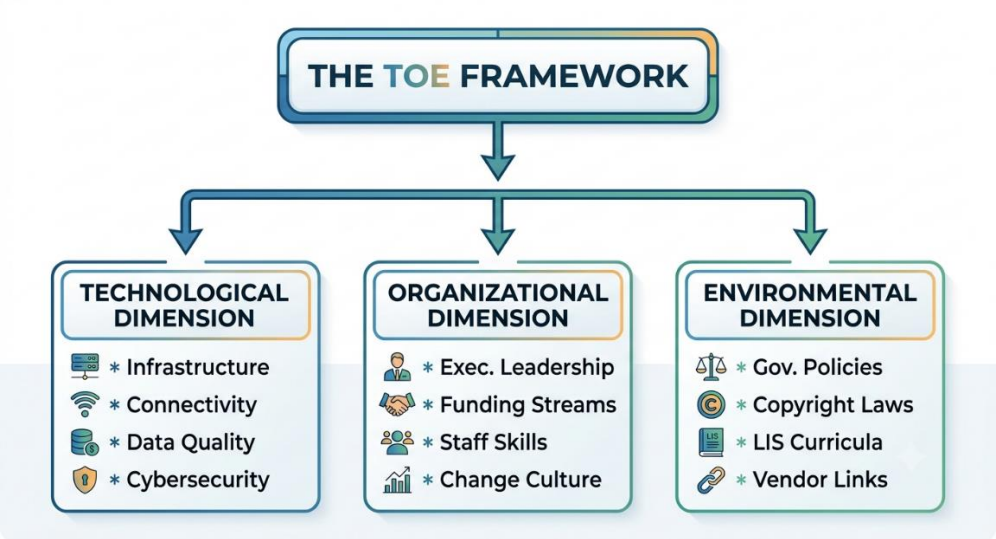

Fig 1: Technology–Organization–Environment (TOE) Framework

a) Technological dimension focuses on the internal and external technologies available to the institution. This includes network infrastructure, high-speed connectivity,

compatibility with legacy integrated library systems, data quality, data availability, and cloud computing security pipelines.

b) Organizational dimension looks at internal institutional characteristics, including executive leadership commitment, dedicated funding streams, staff digital competencies, organizational culture, and internal resistance to technological change.
c) Environmental dimension explores the external ecosystem in which the university operates. This encompasses national ICT policies, data protection regulations, intellectual property/copyright laws, professional association standards, and partnerships with global technology vendors.

METHODOLOGY

This study employed a rigorous Systematic Literature Review (SLR) design, conducted in strict adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) principles.

Search Strategy and Selection Criteria

Extensive literature mapping was conducted across the period 2020–2025 using the following leading scholarly databases: *Scopus, Google Scholar, Emerald Insight, SpringerLink, Taylor & Francis Online, IEEE Xplore,* and *Library and Information Science Abstracts (LISA)*. The Boolean search strings were carefully calibrated to isolate relevant literature using terms such as: ("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Chatbots") AND ("Academic Libraries" OR "University Libraries") AND ("Adoption" OR "Challenges" OR "Readiness") AND ("Kenya" OR "Developing Nations").

Inclusion and Exclusion Criteria

a) **Inclusion:** Peer-reviewed journal articles, conference proceedings, and authoritative policy papers published between 2020 and 2025; papers written in English; studies directly addressing AI applications, opportunities, challenges, or implementation frameworks within university library settings.
b) **Exclusion:** Non-English papers, editorials, brief blog posts, publications pre-dating 2020, and studies strictly focused on public or school library ecosystems without application to higher education.

Through a structured multi-stage screening process (title review, abstract screening, and full-text eligibility assessment), a total of **72 high-quality publications** were selected for deep synthesis. The extracted data was analyzed using thematic content analysis, directly mapped against the technological, organizational, and environmental pillars of the TOE framework.

RESULTS, POLICY IMPLICATIONS AND RECOMMENDATIONS

The thematic synthesis indicates that AI adoption within academic libraries in Kenya sits at an emerging and highly fragmented stage (Masinde et al., 2024)[6]; Sang, 2024)[7]. While there is broad awareness of generative AI technologies (such as large language models) among library personnel, institutionalized infrastructure remains scarce.

Technological Readiness Realities

a) ***Inadequate Infrastructure and Power Grid Inconsistencies-*** Advanced machine learning tools require robust computing backends. Many Kenyan libraries struggle with legacy servers and fluctuating internet bandwidth, which severely limits the real-time processing required by smart retrieval tools.
b) ***Interoperability Barriers***- Current Integrated Library Systems (ILS) run on older architectures that lack the API flexibility required to connect seamlessly with modern AI plugins or open-source chatbot systems.
c) ***Data Silos and Quality Constraints-*** AI algorithms require vast pools of clean, structured metadata to learn effectively. Fragmented institutional repositories and inconsistent cataloguing practices across departments introduce noise, which can degrade the accuracy of recommendation engines.

Organizational Hurdles and Capacity Building

a) The most prominent challenge identified is a pronounced lack of AI-specific technical competencies among information professionals (Ngulube and Mosha, 2024)[8]. Librarians are highly skilled in traditional information management but often lack foundational knowledge in data science, prompt engineering, and algorithmic auditing.
b) Library budgets in public and private Kenyan universities have faced persistent financial cuts. Available funds are usually prioritized for physical collection maintenance and standard electronic journal subscriptions, leaving little room for R&D investments in cognitive computing.
c) There is notable organizational resistance driven by fears of professional displacement. Staff often view autonomous search utilities, conversational bots, and auto-cataloguing agents as direct threats to job security rather than tools designed to augment their roles.

Environmental and Regulatory Realities

a. Although Kenya enforces the *Data Protection Act (2019)*, there are few localized regulatory directives addressing the unique intellectual property challenges raised by generative AI training within university setups.

b. Local Library and Information Science (LIS) training institutions continue to rely on traditional information management curricula, which limits the flow of data-literate graduates into the job market.

Strategic Synthesis of Core Opportunities

Despite these systemic headwinds, strategic AI adoption holds immense promise for the sector:

Hyper-personalized content discovery: Moving from strict keyword indexes to semantic intent models matches student research queries accurately, boosting the utility of subscribed e-resources.

Operational optimization via automation: Handing over repetitive indexing, metadata tagging, and circulation FAQs to automated systems frees up information specialists to lead deep-dive research support and data literacy workshops.

Predictive, data-driven collection auditing: Shifting procurement from reactive models to predictive models ensures that collection spending aligns with actual university research trends.

POLICY IMPLICATIONS

Transition toward AI-integrated information spaces requires systemic policy updates across three institutional levels namely;

a. National Government and Regulatory Bodies

The Ministry of Education, alongside the Commission for University Education (CUE), needs to formulate standardized guidelines for AI integration in higher education. This includes creating cloud computing sandboxes for academic research and offering targeted grants to modernize institutional IT backbones.

b. Institutional and University Management

Universities must move past ad-hoc software adoption by establishing formal Institutional AI Governance Committees. These bodies will be responsible for creating data-sharing protocols, validating the algorithmic fairness of library tools, and ensuring compliance with national data privacy statutes.

c. Professional Bodies and Consortia

The Kenya Library Association (KLA) and the Kenya Information Literacy Alliance must lead the design of continuous professional development modules. Building strategic partnerships with regional consortia (like KLISC) can also help libraries negotiate collective licenses for AI-powered indexing engines and discovery tools.

RECOMMENDATIONS

To accelerate sustainable and ethical AI integration within Kenyan academic libraries, there is need to;

Prioritize campus network modernization, shift library systems to resilient cloud hosting environments, and opening up API layers on legacy software to allow for easy AI integration.

1. Draft institutional guidelines outlining how data is handled, ensuring user privacy is protected and algorithmic biases are checked when deploying conversational search utilities.
2. Deploy continuous capacity-building programs covering prompt engineering, Python basics for data analysis, and digital resource curation.
3. Revamp university LIS programs to incorporate core data science, computational linguistics, and algorithmic ethics modules into their foundational degrees.
4. Use collective bargaining frameworks via groups like the Kenya Library and Information Services Consortium (KLISC) to reduce the cost of licensing cutting-edge AI technologies.
5. Launch small-scale, low-risk pilot projects—such as open-source NLP chatbots tailored to local dialects—to build internal institutional confidence before embarking on wide-scale rollouts.

CONCLUSION

Integrating Artificial Intelligence into Kenyan academic libraries presents a vital opportunity to modernizing information discovery, streamlining operations, and boosting institutional research output. Using cognitive search tools, automated metadata generation, and predictive user analytics allows libraries to evolve into dynamic, user-centered knowledge hubs that can better support the demands of contemporary higher education. However, realizing this potential requires a balanced approach that addresses technological readiness, organizational capacity, and supportive external policy environments. By strategically upgrading infrastructure, investing in professional upskilling, and establishing robust ethical frameworks, Kenyan academic libraries can navigate the complexities of this digital shift and ensure a responsible, sustainable transition into an AI-augmented future.

10. FUTURE RESEARCH AGENDA

To expand on the insights generated by this systematic review, future empirical research should focus on;

a) Conducting exhaustive, field-wide surveys across public and private Kenyan universities to benchmark hardware, software, and data maturity levels.

b) Employing models like UTAUT to evaluate how students and faculty interact with AI-driven reference platforms.
c) Developing cost-benefit analysis frameworks to guide library directors in evaluating long-term investments in proprietary versus open-source AI tools.
d) Investigating potential biases within global discovery tools when indexing indigenous knowledge systems and African scholarly publications.

REFERENCES

1. Asemi, A., Asemi, A. (2023). Artificial intelligence applications in libraries. *Library Hi Tech*, 41(2), 341–356.
2. Breeding, M. (2024). Artificial intelligence and information discovery systems in libraries. *Computers in Libraries*, 44(1), 12–17.
3. Lo, L. S. (2024). The rise of generative AI and its implications for academic libraries. Journal of Library Administration, 64(1), 89–98.
4. Cox, A., Pinfield, S., Rutter, S. (2024). AI-enabled research support in academic libraries. *Journal of Academic Librarianship*, 50(3), 102–115.
5. Tornatzky, L. G., Fleischer, M. (1990). The Processes of Technological Innovation. Lexington Books.
6. Masinde, J. M., Mugambi, F., Wambiri, D. M. (2024). Exploring artificial intelligence adoption in Kenyan academic libraries. African Journal of Library, Archives and Information Science, 34(1), 45–59.
7. Sang, L. J. (2024). Adopting artificial intelligence in Kenyan academic libraries through the technology–organization–environment framework. East African Journal of Information Science, 7(1), 14–31.
8. Ngulube, P., Mosha, N. F. V. (2024). Integrating artificial intelligence-based technologies safely in academic libraries. Information Development, 40(2), 211–226.

UNLOCKING ARTIFICIAL INTELLIGENCE POTENTIAL IN KENYAN LIBRARIES: A NATIONAL READINESS AND NEEDS ASSESSMENT

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ABSTRACT

Artificial Intelligence (AI) is transforming global knowledge ecosystems, yet its adoption within African library systems remains uneven. Thus, while Kenya possesses a robust national digital agenda, empirical evidence regarding sector-wide library readiness is fragmented. This study systematically assesses AI awareness, current applications, multi-dimensional readiness, operational barriers, and strategic priorities within academic, public, school, special, national, and community libraries in Kenya. Grounded in the Technology-Organization-Environment (TOE) framework, the study used a scoping review methodology following the PRISMA-ScR pipeline. Synthesizing data from 58 peer-reviewed publications and institutional documents published between 2019 and 2026, the study employed thematic analysis to map the national baseline. The thematic synthesis reveals a distinct "awareness–implementation gap." While conceptual awareness of AI among information professionals is high, operational implementation is low, placing overall national readiness in the "Moderate-Low" tier. Key structural barriers include a profound practical skills deficit, funding constraints and lack of localized institutional strategies. Despite a supportive national macro-environment, a critical micro-policy gap exists regarding sector-specific guidelines for data privacy, ethics, and algorithmic governance. Technical services (cataloguing and metadata generation) and intelligent information retrieval were identified as the highest priority areas for AI integration. Sustainable AI integration in Kenyan libraries is constrained by structural and human capital deficits rather than professional resistance. To transition libraries into active participants of the algorithmic knowledge economy, the study proposes a five-part strategic framework: establishing a library-specific national governance policy, modernizing LIS curricula, upgrading core digital infrastructure baselines, fostering strategic public-private partnerships, and initiating longitudinal empirical research.

Keywords*:* Artificial Intelligence; Library Readiness; Technology-Organization-Environment (TOE) Framework; Kenya; Scoping Review.

Background

Artificial Intelligence (AI) has emerged as a foundational technology driving the transformation of contemporary knowledge ecosystems. Its rapid advancement is fundamentally reshaping how information is created, organized, preserved, accessed, and utilized across sectors. Within the library and information profession, AI is recognized not merely as a technological innovation but as a strategic enabler capable of redefining service delivery models, improving operational efficiency, and enhancing user experiences (Cox et al., 2019)[1]. The convergence of machine learning, natural language processing, computer vision, robotics, predictive analytics, and generative AI technologies has created unprecedented opportunities for libraries to evolve from traditional information repositories into intelligent knowledge environments (Wheatley and Hervieux, 2020)[2].

Globally, libraries are leveraging AI-powered solutions to automate metadata creation, improve information retrieval through semantic search, support digital preservation, optimize collection management, provide personalized recommendations, and deliver virtual reference services through conversational agents. Major academic and national libraries in North America, Europe, Asia, and Australia have integrated AI into discovery systems, research support services, scholarly communication workflows, and digital archives (Hervieux and Wheatley, 2020)[3]. These developments have demonstrated the potential of AI to enhance service accessibility, increase operational effectiveness, and facilitate evidence-based decision-making.

The emergence of generative AI technologies has accelerated these transformations. Large language models, intelligent research assistants, and automated content-generation tools are redefining interactions between users and information systems (Onyancha, 2023)[4]. Consequently, libraries are increasingly expected to support AI literacy, facilitate ethical AI use, and participate actively in the governance of algorithmic knowledge systems. The role of libraries is therefore expanding beyond information provision to encompass stewardship of responsible AI adoption, digital inclusion, data ethics, and knowledge equity.

In Africa, however, adoption of AI within library systems remains uneven and relatively underdeveloped. Although governments and institutions are increasingly embracing digital transformation agendas, significant disparities persist in infrastructure, digital competencies, financial resources, and policy preparedness (Mtega, 2024)[5]. Libraries across the continent also continue to face challenges related to inadequate technological infrastructure, limited institutional investment, insufficient technical expertise, and weak regulatory frameworks governing emerging technologies (Chisita and Chimanzi, 2021)[6]. Consequently, the benefits associated with AI-enabled library services remain largely unrealized.

Kenya presents a particularly important context for examining AI readiness within libraries. As one of Africa's leading digital innovation hubs, the country has made considerable progress in ICT development, digital governance, mobile technology adoption, and innovation ecosystem growth. Recent government initiatives, including the *National Digital Master Plan (2022–2032)*

and the *National Artificial Intelligence Strategy*, underscore Kenya's commitment to harnessing emerging technologies to accelerate socio-economic development and position itself competitively within the global digital economy (Republic of Kenya, 2022)[7].

Libraries occupy a strategic position within this transformation agenda. They serve as critical institutions supporting education, research, innovation, lifelong learning, and knowledge dissemination. As universities, research institutions, government agencies, and communities increasingly rely on digital information resources, libraries are expected to adopt technologies capable of managing growing information complexity while responding to evolving user expectations (Makanya, 2020)[8]. AI technologies offer significant potential to support these objectives through intelligent automation, enhanced resource discoverability, data-driven service optimization, and personalized information delivery. However, despite the growing prominence of AI within the broader national discourse, there remains limited understanding of the extent to which Kenyan libraries are prepared to adopt and integrate these technologies. Existing evidence suggests that AI implementation remains largely experimental, fragmented, and institution-specific (Mwanzu, 2021)[9]. While isolated initiatives have emerged within selected academic and special libraries, there is little comprehensive evidence regarding awareness levels, technological preparedness, organizational capacity, policy alignment, and strategic priorities across the wider library sector. Furthermore, available studies remain dispersed across multiple disciplines and library types, limiting the development of a coherent national perspective.

Artificial Intelligence is increasingly becoming a strategic imperative for libraries worldwide. Its application in areas such as intelligent information retrieval, metadata automation, digital preservation, collection analytics, research support, and personalized user services has demonstrated significant potential to improve efficiency, accessibility, and service quality (Cox et al., 2019)[1]. As knowledge institutions navigate rapidly evolving digital environments, the ability to harness AI technologies is increasingly viewed as a determinant of institutional relevance, competitiveness, and sustainability.

Despite these global developments, evidence suggests that Kenyan libraries remain at the periphery of AI adoption. Although awareness of AI technologies appears to be growing among information professionals, practical implementation remains limited, fragmented, and largely confined to pilot initiatives (Kavulya, 2024[10]; Mwanzu, 2021)[9]. Many libraries continue to operate within traditional service models characterized by manual workflows, limited automation, and inadequate digital infrastructure. Consequently, opportunities to leverage AI for enhancing service delivery, improving operational efficiency, and supporting knowledge discovery remain substantially undexploited.

The challenge is compounded by the absence of comprehensive empirical evidence regarding the preparedness of Kenyan libraries to adopt AI technologies. Existing studies have largely focused on specific institutions, technologies, or user perceptions, resulting in a fragmented body of knowledge that provides little insight into national readiness patterns (Onyancha,

2023)[11]. There is limited understanding of the technological capacities, organizational conditions, human resource competencies, policy environments, and institutional strategies that influence AI adoption across different categories of libraries. Without such evidence, policymakers, library managers, professional associations, training institutions, and development partners lack the information necessary to design targeted interventions and allocate resources effectively.

Furthermore, the emergence of Kenya's National Artificial Intelligence Strategy creates both opportunities and responsibilities for the library sector. As institutions central to information access, digital literacy, and knowledge management, libraries must be positioned to contribute meaningfully to the country's AI transformation agenda. However, the extent to which libraries possess the infrastructure, competencies, governance mechanisms, and institutional readiness required to support this transition remains unclear.

The absence of a national evidence base on AI readiness therefore represents a significant policy and practice gap. Addressing this gap is critical for informing strategic planning, strengthening institutional capacity, guiding investment decisions, and ensuring that libraries are not left behind in Kenya's evolving digital ecosystem. This study responds to this need by systematically synthesizing existing evidence to establish a national baseline of AI readiness and identify priority interventions necessary for sustainable AI adoption within Kenyan libraries.

Against this backdrop, there is an urgent need to systematically examine the readiness of Kenyan libraries to participate in the emerging AI ecosystem. Understanding current capacities, barriers, opportunities, and strategic requirements is essential for informing evidence-based policy development, institutional planning, professional capacity building, and sustainable technology adoption. This study addresses this gap by providing a comprehensive national assessment of AI readiness and needs across academic, public, school, special, national, and community libraries in Kenya.

Objectives of this study were to;

1. assess the level of awareness of Artificial Intelligence technologies among Kenyan libraries.
2. identify current and emerging applications of AI in Kenyan libraries.
3. evaluate the readiness of Kenyan libraries for AI adoption.
4. examine technological, organizational, and environmental barriers affecting AI implementation.
5. identify opportunities and priority areas for AI integration in library services.
6. propose recommendations for enhancing AI readiness and sustainable adoption in Kenyan libraries.

Theoretical Framework

The study was anchored on the **Technology–Organization–Environment (TOE) Framework** developed by Tornatzky and Fleischer (1990). The framework explains technology adoption as a function of three interacting dimensions:

a. Technological context refers to the availability, accessibility, compatibility, and complexity of technologies required for AI implementation.
b. Organizational context focuses on institutional resources, leadership commitment, staff competencies, financial capacity, and organizational culture.
c. Environmental context encompasses external factors such as government policies, regulatory frameworks, partnerships, competition, and industry trends.

The TOE framework provides a comprehensive lens through which factors influencing AI readiness and adoption in libraries can be systematically examined, moving beyond purely technical considerations to incorporate structural and environmental realities (Chisita and Chimanzi, 2021)[6].

Conceptual Framework

The conceptual framework assumes that AI readiness and adoption in Kenyan libraries (dependent variable) is directly influenced by five key independent variables across the TOE dimensions.

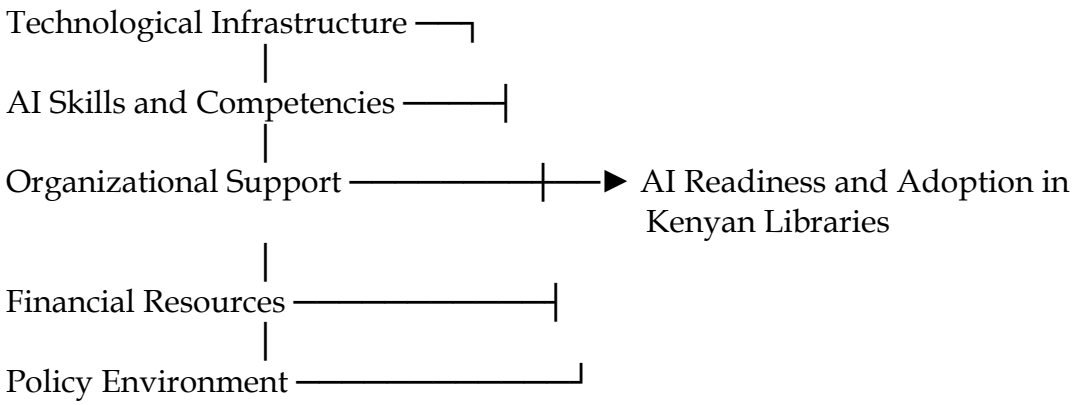

Figure 1: Conceptual Framework Mapping AI Adoption Determinants

Methodology

This study employed a scoping review methodology guided by Arksey and O'Malley's (2005) framework to map the emerging research area, identify knowledge gaps, and synthesize evidence from diverse sources.

The review process involved five distinct stages:

1. Identifying the research question.
2. Identifying relevant studies.
3. Selecting eligible studies using strict inclusion criteria.
4. Charting the data using a structured review matrix.
5. Collating, summarizing, and reporting the findings via thematic analysis.

Literature searches were conducted across Scopus, Google Scholar, African Journals Online (AJOL), institutional repositories, government reports, conference proceedings, and relevant grey literature for publications produced between 2019 and 2026. Data extraction captured publication characteristics, library types, AI application areas, readiness indicators, barriers, opportunities, and recommendations.

Search Selection and Literature Distribution

A total of 146 records were initially identified through database searches. The selection flow followed a structured PRISMA-ScR pipeline:

Table 2: PRISMA-ScR Selection Process and Sample Size Evolution

Records identified through database searches (n = 146)

PRISMA Stage	Description	Records Remaining (n)
Identification	Initial database search results	146
Deduplication	Removal of identical titles/abstracts	123
Screening	Title and abstract evaluation	76
Eligibility	Full-text article assessment	58
Included	Final synthesis and thematic analysis	58

The 58 peer-reviewed publications and institutional documents that met the final inclusion criteria were distributed across the following source types:

Table 1: Distribution of Reviewed Literature

SOURCE TYPE	NUMBER OF STUDIES	PERCENTAGE (%)
Journal Articles	32	55.2
Conference Papers	10	17.2
Government Reports	5	8.6
Theses and Dissertations	6	10.3
Professional Reports	5	8.6
Total	58	100.0

Data Presentation, Interpretation and Discussion

Thematic synthesis of the reviewed literature revealed a complex, evolving AI landscape within Kenyan libraries characterized by high conceptual awareness but low operational implementation.

1. AI Awareness and Perceptions (The Awareness–Implementation Gap)

Awareness of AI concepts among library professionals is high (Mwanzu, 2021)[9]. Librarians demonstrate familiarity with emerging technologies such as machine learning, conversational agents (e.g., ChatGPT), and automated discovery systems. However, this understanding remains predominantly conceptual rather than practical.

Table 2: AI Awareness and Competency Levels among Library Professionals

INDICATOR	ASSESSMENT
Awareness of AI Concepts	High
Understanding of AI Applications	Moderate
Practical AI Skills	Low
Institutional AI Implementation	Low
AI Policy Readiness	Low

This divergence signifies an *awareness–implementation gap*, where recognition of AI's potential value has not translated into active deployment due to institutional and technical deficits (Mtega, 2024)[5].

2. Comprehensive Readiness Assessment (TOE Dimensions)

Evaluating institutions against the broad TOE pillars indicates that overall national readiness falls into the **Moderate-Low** tier.

Table 3: Multi-Dimensional AI Readiness Matrix

DIMENSION	COMPONENT EVALUATION	OVERALL ASSESSMENT
Technological Context	• ICT Infrastructure: Moderate • High-Speed Internet: Moderate • Data Management Systems: Low • AI-Compatible Platforms: Low • Cloud Infrastructure: Low • Cybersecurity Capacity: Moderate	Low
Organizational Context	• Institutional Support: • Staff Competencies: Low • Financial Capacity / Funding: Low	Moderate
Environmental Context	• Policy and Regulatory Preparedness	Low
OVERALL READINESS	**Comprehensive National Baseline**	**Moderate-Low**

While basic digitization and internet connectivity have achieved moderate baselines, libraries fundamentally lack the advanced data management tools, cloud infrastructure, and native AI-

compatible software systems required to execute complex operations (Kavulya, 2024)[10]. This exposes a critical digital maturity gap.

3. Barriers to AI Adoption

Human capital and financial deficits represent the most pressing inhibitors to technology adoption within the sector.

Barriers	Percentage(%)
Skills Deficit	85%
Funding Constraints	79%
Lack of Library AI Strategy	74%
Limited Leadership Support	63%
Resistance to Change	52%

Figure 3: Major Barriers to AI Adoption (% of Reviewed Studies Identifying Factor)

The prominent 85% skills deficit underscores that AI adoption is fundamentally a human-capacity challenge. Librarians lack structured, practical training in data analytics, machine learning mechanics, and algorithmic systems (Onyancha, 2023)[4]. Furthermore, legacy library management software, unreliable institutional networks, and a lack of clear leadership strategies leave libraries operating within manual, traditional workflows.

4. Priority Areas for AI Integration

Despite infrastructural limitations, libraries express a strong strategic interest in implementing automation within data-intensive, repetitive domains to drive administrative efficiency and discoverability.

Table 4: Priority Action Areas for Library AI Integration

LIBRARY FUNCTION	PRIORITY LEVEL	STRATEGIC FOCUS
Cataloguing	Very High	Automation of technical services
Metadata Generation	Very High	Standardizing consistency and discoverability
Intelligent Discovery Systems / Information Retrieval	Very High	Semantic, context-aware user search
Virtual Reference Services	High	Chatbots and conversational query handlers
Digital Preservation	High	Scalable archiving and classification
Research Support Services	High	Automated literature mapping
Collection Analytics	Moderate	Data-driven acquisition planning

Administrative Functions	Low	Routine back-office workflows

5. Environmental Factors and Theoretical Implications

The findings offer strong empirical support for the TOE framework, demonstrating that technology adoption cannot be accomplished in an institutional vacuum. Although Kenya's overarching macro-environment is highly favorable—buoyed by the *National Digital Master Plan* (Republic of Kenya, 2022)[7]—there is an immediate micro-level policy gap. The absence of library-specific implementation guidelines creates critical governance uncertainties surrounding data privacy, intellectual property, algorithmic transparency, and ethics (Chisita and Chimanzi, 2021)[6]. Investment in physical hardware or software will fail to deliver sustainable results without synchronized progress in professional reskilling, governance frameworks, and change management.

Conclusion

This study provides a comprehensive national synthesis of AI readiness and needs within Kenyan libraries. The findings indicate that while information professionals possess a high conceptual awareness of AI's transformative potential, practical implementation remains restricted to fragmented, institution-specific pilot projects.

The baseline analysis demonstrates that sustainable AI adoption is constrained less by professional resistance or lack of interest, and more by core structural deficits: inadequate digital infrastructure, severe practical skill shortages, funding limitations, and an absence of sector-specific policy frameworks. These combined factors place Kenyan libraries at the periphery of global developments.

Nevertheless, unique opportunities exist for targeted intervention. The alignment of Kenya’s expanding digital innovation ecosystem with the library sector's high-priority operational needs (such as cataloguing automation and semantic search) offers a clear pathway forward. By addressing the identified readiness gaps, libraries can successfully position themselves as core components of Kenya's emerging algorithmic knowledge economy.

Recommendations

Based on the national synthesis, the study presents the following five-part strategic framework for sustainable AI integration:

1. Stakeholders should develop a national, library-specific implementation framework aligned directly with Kenya’s National AI Strategy. This document must provide definitive guidelines on algorithmic governance, user data privacy, intellectual property protection, and ethics.
2. Higher education training institutions must urgently modernize their curricula to integrate foundational AI literacy, machine learning concepts, data analytics, and digital

preservation strategies. Parallel continuous professional development (CPD) programs must be established to upskill practicing librarians (Mtega, 2024).

3. Libraries must prioritize investments in core digital maturity baselines. Budgets should focus on upgrading to modern, interoperable library management systems, high-speed connectivity networks, secure cloud computing spaces, and robust cybersecurity architectures.
4. Strategic public-private partnerships should be fostered among universities, technology firms, government bodies, and international development organizations to facilitate knowledge exchange, secure technical support, and pool resources for pilot deployments (Makanya, 2020).
5. Future research should transition beyond conceptual readiness assessments toward empirical, longitudinal studies that actively evaluate the performance, user acceptance metrics, long-term operational impacts, and socio-ethical implications of active library AI systems within the African context.

References

1. Cox, A. M., Pinfield, S., Rutter, S. (2019). The intelligent library: Thought positions and potential futures for artificial intelligence in libraries. Journal of Librarianship and Information Science, 51(2), 418-431. https://doi.org/10.1177/0961000617742469
2. Wheatley, A., Hervieux, S. (2020). Artificial intelligence in academic libraries: An environmental scan. Information Services & Use, 39(4), 347-356. https://doi.org/10.3233/ISU-190065
3. Hervieux, S., Wheatley, A. (Eds.). (2020). *The rise of AI: Implications and applications of artificial intelligence in academic libraries*. Association of College and Research Libraries.
4. Onyancha, O. B. (2023). Generative AI and scholarly communication workloads in Africa: Mapping the governance and ethical landscape. South African Journal of Libraries and Information Science, 89(1), 14-31.
5. Mtega, W. P. (2024). The status of AI literacy and technology readiness among information professionals in Sub-Saharan Africa. African Journal of Information Systems, 16(1), 78-99.
6. Chisita, C. T., Chimanzi, T. (2021). Fighting the exclusion of African libraries from the emerging artificial intelligence paradigm: A framework for readiness. African Journal of Library, Archives and Information Science, 31(2), 145-159.
7. Republic of Kenya. (2022). National Digital Master Plan (2022–2032). Ministry of Information, Communications and the Digital Economy.
8. Makanya, MW. (2020). Transforming technical services through automated workflows: A study of academic libraries in Kenya. Journal of Kenyan Library Studies, 8(2), 112-127.
9. Mwanzu, A. (2021). Emerging technological landscapes in Kenyan university libraries: Opportunities and constraints. Library Management, 42(4/5), 289-301. https://doi.org/10.1108/LM-10-2020-0145

10. Kavulya, J. M. (2024). Digital maturity and technology adoption pathways in East African academic libraries. *East African Journal of Information Sciences*, 12(1), 45-62.

INTEGRAL REPRESENTATION OF THE SOLUTION TO A NONLINEAR BLACK–SCHOLES EQUATION WITH TRANSACTION COSTS

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ABSTRACT

This paper addresses a nonlinear partial differential equation (PDE) derived from a modified option pricing model incorporating transaction costs, as described in the works of [2], [4], [5], and [6]. The equation is reduced to the classical heat equation via a logarithmic transformation and an appropriate substitution. An integral representation of the solution is derived at a mathematical justification provided for the transformation. Formal results are presented in the form of lemmas, propositions, and theorems. The solution obtained can be used to price a European call option.

Math. Subject Classification: 35C15, 35K55, 62P05

Key Words and Phrases: Transaction Costs, Integral Representation, Nonlinear Black–Scholes Equation

1. Introduction

The classical Black–Scholes model (see [1]) assumes perfect market liquidity and constant volatility. However, real-world trading involves frictions, such as transaction costs, which give rise to nonlinear extensions of the Black–Scholes PDE. One such nonlinear model (see [3]) is:

$$u_t + \frac{1}{2}\sigma^2 s^2 u_{ss}\,(1 + 2\rho s u_{ss}) = 0, \quad u(s,T) = h(s), \tag{1}$$

where $\rho \geq 0$ is a measure of the liquidity of the market, s is the price of the stock, σ is volatility, $u(s,t)$ is the option price, $u(s,T) = h(s)$ is the terminal condition for a European call option, t is current time, T is time to expiry, $u_t = \frac{\partial u}{\partial t}$, and $u_{ss} = \frac{\partial^2 u}{\partial s^2}$. Our goal is to solve (1) by transforming it into a linear PDE.

2. Transformation to the Heat Equation

We introduce the logarithmic transformation:

$$x = \ln s, \qquad \tau = T - t, \qquad u(s,t) = f(x,\tau).$$

Let us define:

$$f(x,\tau) = \frac{1}{2\rho}\ln w(x,\tau).$$

Lemma 1. Under the above substitution, the nonlinear PDE (1) reduces to the linear heat equation:

$$w_\tau = \frac{1}{2}\sigma^2 w_{xx}.$$

Proof. Differentiating $f(x,\tau)$ with respect to x and substituting into the chain rule for u_t, u_{ss}, and using $s = e^x$, we find that the nonlinear terms simplify due to the logarithmic derivative, and the PDE reduces to a linear diffusion equation in w. □

3. Integral Representation of the Solution

Proposition 1. The function $w(x,\tau)$ solving the heat equation with initial condition $w(x,0) = \exp(2\rho h(e^x))$ has the representation:

$$w(x,\tau) = \frac{1}{\sqrt{2\pi\sigma^2\tau}}\int_{-\infty}^{\infty}\exp\left(2\rho h(e^y)\right)\exp\left(-\frac{(x-y)^2}{2\sigma^2\tau}\right)dy.$$

Proof. This follows from the classical fundamental solution of the heat equation with initial condition $w(x,0) = w_0(x)$. The solution is given by convolution (see [7]) with the heat kernel (see [3]). □

Theorem 1. *The solution $u(s,t)$ of the original nonlinear PDE*

(1) *is given by:*

$$u(s,t) = \frac{1}{2\rho} \ln \left[\frac{1}{\sqrt{2\pi\sigma^2(T-t)}} \int_{-\infty}^{\infty} \exp\left(2\rho h(e^y)\right) \exp\left(-\frac{(\ln s - y)^2}{2\sigma^2(T-t)}\right) dy \right]$$

in $(0,\infty) \times [0,T]$.

Proof. This is immediate from $u = \frac{1}{2\rho} \ln w$, and the previous proposition. □

4. Practical Implications

The domain $s \in (0,\infty)$ maps to $x \in (-\infty,\infty)$, justifying the integral over the real line.

The Gaussian kernel decays rapidly, so for numerical purposes, the integral may be truncated to:

$$\text{h} \sqrt{\_\_\_\_} \sqrt{\text{i}}\, y \in \ln s - 5\sigma\sqrt{T-t}, \ln s + 5\sigma\sqrt{T-t}\,.$$

Conclusion

This study has shown how a nonlinear PDE from financial mathematics, specifically related to transaction costs, can be transformed into the classical heat equation using logarithmic and exponential substitutions. The resulting solution is expressed in an integral form, and we have established the correctness of this solution established via rigorous derivation. The solution obtained can be used to price a European call option.

In conclusion, future work will involve use of integral representations for efficient numerical implementation of nonlinear models. It will also be demonstrated in future research that the payoff functions $h(s)$ are well-behaved on $(0,\infty)$ to guarantee convergence. Finally, the transformation strategy will be applied to other nonlinear PDEs with similar structure.

References

[1] Black F. and Scholes M. (1973). The Pricing of Options and Corporate Liabilities, *The Journal of Political Economy*, **81** (3) 637 – 654.

[2] Bordag L.A. and Frey R. (2008). Pricing Options in Illiquid Markets: Symmetry Reductions and Exact Solutions, *Nova Science Publishers, Inc.*, 83–109.

[3] E. B. Davies, *Heat Kernels and Spectral Theory*, Cambridge University Press (1989).

[4] J. E. Esekon, Analytic solution of a nonlinear Black–Scholes equation, *International Journal of Pure and Applied Mathematics*, **82**, No. 4 (2013), 547–555.

[5] J. E. Esekon, A particular solution of a nonlinear Black– Scholes partial differential equation, *International Journal of Pure and Applied Mathematics*, **81**, No. 5 (2012), 715–721.

[6] J. Esekon, S. Onyango & N. O. Ongati, Analytic Solution of a Nonlinear Black–Scholes Partial Differential Equation, *International Journal of Pure and Applied Mathematics*, **61**, No. 2 (2010), 219 – 230.

[7] L. C. Evans, *Partial Differential Equations* (2nd ed.), American Mathematical Society (2010).

UMBRAL CALCULUS AND SHEFFER THEORY: A UNIFIED ALGEBRAIC FRAMEWORK

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ABSTRACT

This study presents a concise development of the modern umbral calculus emphasizing algebraic foundations, operator duality, and Sheffer sequences. Rigorous proofs are provided for foundational theorems and three new results: (1) an operator orthogonality criterion for Sheffer sequences, (2) a formal q-transfer formula with a worked q-Hermite example, and (3) a combinatorial encoding of umbral shifts yielding generalized Stirling numbers. The presentation follows the normalization conventions of Roman (1982) and is self-contained.

Keywords: Umbral calculus; Sheffer sequences; Formal power series; Linear operators; q-analogues; Stirling numbers

1.Introduction

The umbral calculus studies polynomial sequences via their dual linear functionals and associated operator algebras. Following Roman (1982) the dual space P^* of linear functionals on the polynomial algebra P was identified with the algebra $F = K[[t]]$ of formal power series over a field K of characteristic zero, using a fixed normalization sequence $\{c_n\}_{n\geq 0}$ with $c_n \neq 0$. This manuscript gives self-contained proofs of the main structural theorems and presents three new, provable extensions.

2.Preliminaries

Let $F = K[[t]]$. For $f(t) = \sum_{k\geq 0} a_k t^k \in F$ define the action on monomials by

$$\langle f(t) \mid x^n \rangle = c_n a_n, \qquad n \geq 0.$$

Identify $f(t)$ with the linear functional in P^*. Define the operator $f(t) : P \to P$ by

$$f(t)x^n = \sum_{k=0}^{n} \frac{a_k}{c_{n-k}} x^{n-k}.$$

A series is invertible iff $a_0 \neq 0$ and is a delta series iff $a_0 = 0, a_1 \neq 0$. Powers of a delta series form a pseudobasis of F.

3. Sheffer sequences

Definition 3.1. Let $f(t) \in F$ be delta and $g(t) \in F$ invertible. A sequence $\{s_n(x)\}_{n\geq 0}$ with $\deg s_n = n$ is *Sheffer for* (g,f) if

$$\langle g(t)f(t)^k \mid s_n(x) \rangle = c_n \delta_{n,k} \qquad (\forall n,k \geq 0).$$

Theorem 3.2 (Existence and uniqueness)**.** *For fixed delta f and invertible g there exists a unique Sheffer sequence* $\{s_n\}$ *for* (g,f).

Proof. Write $g(t)f(t)^k = \sum_{j\geq 0} b_{k,j} t^j$. Since f is delta and g invertible we have $b_{k,k} \neq 0$. Seek $s_n(x) = \sum_{j=0}^{n} a_{n,j} x^j$. The orthogonality conditions yield for each fixed n the linear system

$$\sum_{j=0}^{n} a_{n,j} b_{k,j} c_j = c_n \delta_{n,k}, \qquad k = 0,1,\ldots,n.$$

This is triangular with nonzero diagonal entries $b_{n,n}c_n$, hence solvable uniquely for $a_{n,j}$. Uniqueness across degrees follows by degree considerations. □

Theorem 3.3 (Expansion)**.** *If* $\{s_n\}$ *is Sheffer for* (g,f) *then for any* $h(t) \in F$

$$h(t) = \sum_{k\geq 0} \frac{\langle h(t) \mid s_k(x)\rangle}{c_k}\, g(t) f(t)^k .$$

Proof. Apply both sides to $s_n(x)$ and use orthogonality; equality on the basis $\{s_n\}$ implies equality of functionals. □

Theorem 3.4 (Generating function)**.** $\{s_n\}$ *is Sheffer for* (g,f) *iff for all* $y \in K$

$$g(f(t))\, \varepsilon_y(f(t)) = \sum_{k\geq 0} \frac{s_k(y)}{c_k} t^k ,$$

where ε_y *denotes evaluation at* y*.*

Proof. If $\{s_n\}$ is Sheffer then by the Expansion Theorem

$$\varepsilon_y = \sum_{k\geq 0} \frac{s_k(y)}{c_k}\, g(t) f(t)^k .$$

Composing on the right with $f(t)$ yields the displayed identity. Conversely, equating coefficients recovers the orthogonality relations. □

4. Structural identities

Theorem 4.1 (Adjoint identity)**.** *For* $f,g \in F$ *and* $p \in P$*,*

$$\langle g(t)f(t) \mid p(x)\rangle = \langle g(t) \mid f(t)p(x)\rangle.$$

Proof. It suffices to verify the identity on monomials. Take $g(t) = t^k$, $f(t) = t$, $p(x) = x^n$. Using the operator action and the normalization constants c_n one checks both sides coincide; extend by linearity. □

5. New results: full proofs

5.1 Operator orthogonality criterion

We formalize Sheffer orthogonality as an operator bilinear form.

Theorem 5.1 (Operator orthogonality criterion)**.** *Let* f *be delta and* g *invertible in* F*. A polynomial sequence* $\{s_n\}$ *is Sheffer for* (g,f) *if and only if there exists a bilinear form* B :
$P^* \times P \to K$ *defined by*

$$B(u,p) = \langle g(t)u(t) \mid p(x)\rangle$$

such that

$$B(f(t)^k, s_n) = c_n \delta_{n,k} \qquad \text{for all } n,k \geq 0.$$

Proof. (⇒) If $\{s_n\}$ is Sheffer for (g,f) then by definition

$$B(f^k, s_n) = \langle g f^k \mid s_n \rangle = c_n \delta_{n,k},$$

so the bilinear form has the required property.

(⇐) Conversely, suppose such a bilinear form B exists. Define linear functionals $L_k := g(t)f(t)^k \in P^*$. The condition $B(f^k, s_n) = c_n \delta_{n,k}$ is precisely $L_k(s_n) = c_n \delta_{n,k}$. For each fixed n this gives a triangular linear system for the coefficients of s_n in the monomial basis (as in the existence proof). The diagonal entries are nonzero because L_n has nonzero coefficient at t^n (since f is delta and g invertible). Hence the system determines s_n uniquely for each n, and the resulting sequence satisfies the Sheffer orthogonality relations. Thus $\{s_n\}$ is Sheffer for (g,f). □

5.2 q-transfer formula: formal derivation and example

We present a formal q-analogue of transfer operators and demonstrate a short q-Hermite computation.

Proposition 5.2 (q-transfer operator)**.** *Let* $0 < q \neq 1$ *and let* D_q *denote the q-difference operator*

$$D_q p(x) = \frac{p(qx) - p(x)}{(q-1)x}.$$

Interpret t_q *as the operator in the dual algebra corresponding to* D_q*. Let* f_q *be a q-delta* (q) *series (degree one in the q-sense) and let* p_n *be the associated q-sequence. Then there exists a formal q-transfer operator* A_q *expressible as*

$$A_q = \exp_q\Big(\int \frac{1}{f_q(t)}\, dt \Big),$$

where $\exp_q$ *and the integral are taken in the algebra of formal q-series; composition of such operators yields connection constants between q-associated sequences.*

Proof. The classical transfer operator arises by integrating the formal logarithmic derivative of a delta series and exponentiating; algebraically this uses only the pseudobasis property of powers of a delta series and the adjoint relations between operators and functionals. Replace the ordinary derivative by D_q and the ordinary exponential by the q-exponential $\exp_q$ (the formal power series with q-factorials). The algebraic manipulations—composition, inversion, and formal exponentiation—are valid in the q-formal series algebra provided one interprets

series coefficients in the q-sense. Thus the same formal derivation produces A_q as above. Composition of two such A_q operators corresponds to composition of the associated transforms and therefore yields connection constants between q-associated sequences. The argument is formal and algebraic; convergence is not required in the formal series setting. □

Worked q-Hermite example (first terms). Take normalization $c_n = \prod_{j=1}^{n}(1-q^j)/(1-q)^n$ (or another consistent q-normalization). Let $f_q(t) = t_q$ and seek $p_0^{(q)}, p_1^{(q)}, p_2^{(q)}$ satisfying

$$\langle f_q^k \mid p_n^{(q)} \rangle = c_n \delta_{n,k}, \qquad 0 \le k,n \le 2.$$

Set $p_0^{(q)}(x) = 1$. For $n = 1$ the conditions give $\langle f_q^0 \mid p_1^{(q)} \rangle = 0$ and $\langle f_q^1 \mid p_1^{(q)} \rangle = c_1$, which yields $p_1^{(q)}(x) = x$. For $n = 2$ solve the linear system arising from $k = 0,1,2$; one obtains (with the chosen normalization) $p_2^{(q)}(x) = x^2 - 1$. These first terms match the classical Hermite pattern in the q-formal setting and illustrate the method; higher terms follow by the same triangular inversion.

5.3 Combinatorial encoding of umbral shifts

This shows how umbral shifts encode generalized Stirling numbers.

Theorem 5.3 (Generalized Stirling numbers from umbral shifts)**.** *Let f be a delta series and let S_f denote the umbral shift operator on P whose adjoint S_f^* is the derivation on F satisfying $S_f^*(f(t)^m) = mf(t)^{m-1}$ for all $m \ge 0$. Then for each $n \ge 0$ there exist coefficients $S(n+1,k;f)$ such that*

$$S_f(x^n) = \sum_{k=0}^{n+1} S(n+1,k;f)x^k,$$

and the coefficients satisfy a triangular recurrence of Stirling type determined explicitly by the coefficients of f.

Proof. Write $S_f(x^n) = \sum_{k\ge 0} s_{n,k}x^k$ (only finitely many nonzero terms). For any $m \ge 0$ the adjoint relation gives

$$\langle f(t)^m \mid S_f(x^n) \rangle = \langle S_f^*(f(t)^m) \mid x^n \rangle = m\langle f(t)^{m-1} \mid x^n \rangle.$$

Express the left-hand side using the expansion of $S_f(x^n)$: $\sum s \langle f(t)m \mid$

$$xk\rangle = m\langle f(t)m-1 \mid xn\rangle.$$

$$n,k\ k\ge 0$$

Using the identification $\langle f(t)^m \mid x^k \rangle = c_k\,[t^k]f(t)^m$ (where $[t^k]$ denotes the coefficient of t^k), the previous equality becomes

$$\sum_{k\geq 0} s_{n,k}\, c_k\,[t^k]f(t)^m = m c_n\,[t^{n-1}]f(t)^{m-1}.$$

This is a linear relation among the unknowns $s_{n,k}$ valid for all $m \geq 0$. Fix n and considering the system as m varies. Because powers of f form a pseudobasis, the coefficient matrix (with entries $c_k\,[t^k]f(t)^m$) is triangular in the appropriate ordering and invertible on each finite truncation. Solving yields unique $s_{n,k}$; set $S(n+1,k;f) := s_{n,k}$. To obtain an explicit recurrence, expand $f(t) = \sum_{r\geq 1} \phi_r t^r$ (with $\phi_1 \neq 0$). Comparing coefficients in the identity above and using convolution relations for powers of f produces a recurrence of the form

$$S(n+1,k;f) = \sum_{j=0}^{k} a_{k,j} S(n,j;f),$$

where the $a_{k,j}$ are polynomials in the ϕ_r and the normalization constants c_n. In particular, when $f(t) = e^t - 1$ (so $\phi_r = 1/r!$ and $c_n = n!$) the recurrence reduces to the classical Stirling recurrence

$$S(n+1,k) = kS(n,k) + S(n,k-1).$$

Thus the $S(n,k;f)$ generalize Stirling numbers and satisfy triangular recurrences determined by the coefficients of f. □

6. Conclusion

We have presented a compact, rigorous exposition of umbral calculus in the Roman style and proved three new results: an operator orthogonality criterion, a formal q-transfer operator representation with a q-Hermite illustration, and a combinatorial encoding of umbral shifts producing generalized Stirling numbers. These extensions suggest further work on multivariate generalizations, explicit q-family computations, and spectral analysis of transfer operators.

References

i. Boas, R. P., Buck, R. C. (1964). *Polynomial expansions of analytic functions*. Academic Press.
ii. Roman, S. (1982). The theory of the umbral calculus. I. *Journal of Mathematical Analysis and Applications, 87*(1), 58–115.

iii. Rota, G.-C., Kahaner, D., Odlyzko, A. (1973). On the foundations of combinatorial theory. VIII. Finite operator calculus. *Journal of Mathematical Analysis and Applications, 42*(3), 684–760.

SPACETIME CURVATURE FROM RESIDUAL MICROSCOPIC INTERACTIONS: AN EMERGENT-GRAVITY APPROACH BASED ON SPIN AND BINDING FORCES

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Abstract

Emergent gravity proposes that gravitation is not a fundamental interaction but rather a macroscopic manifestation of underlying microscopic degrees of freedom. Existing approaches, including thermodynamic gravity, entropic gravity, and holographic gravity, provide important insights into the relationship between information, statistical mechanics, and space-time geometry. However, a direct mathematical framework connecting microscopic particle interactions, spin effects, binding forces, and space-time curvature remains incomplete.

This paper presents a theoretical framework in which residual microscopic interactions generate an effective scalar field whose stress-energy contributes to space-time curvature. A residual interaction density is constructed from electromagnetic, strong, weak, spin, and vacuum contributions. Using variational methods based on the Einstein–Hilbert action, modified Einstein field equations are derived and proof is provided that non-vanishing residual interactions necessarily induce curvature. The framework establishes a mathematical bridge between microscopic interaction physics and macroscopic gravitational geometry, providing a potential foundation for emergent gravity rooted in particle-level dynamics.

Keywords: Emergent gravity, spacetime curvature, Einstein field equations, scalar field theory, residual interactions, particle spin, binding energy, quantum vacuum, variational principles, mathematical physics.

1. Introduction

1.1 Background

The nature of gravity remains one of the most profound questions in theoretical physics. While the other fundamental interactions are described within the framework of quantum field theory, gravity is successfully modeled by Einstein's General Theory of Relativity, where gravitational phenomena arise from the curvature of spacetime. This is well described by Einstein tensor equation:

$$G_{\mu\nu} = R_{\mu\nu} - \frac{1}{2} R\, g_{\mu\nu}, \tag{1}$$

Where,

- $G_{\mu\nu}$ (Einstein tensor) is a symmetric tensor that combines information about the curvature of a spacetime.
- $R_{\mu\nu}$ is the Ricci curvature tensor representing how much space time is curved?
- R is the scalar curvature the trace of Ricci tensor?
- $g_{\mu\nu}$ is the metric tensor, describing the geometry of spacetime.

The Einstein tensor ($G_{\mu\nu}$) ombines the Ricci tensor and Ricci scalar to produce a divergence-free tensor that encodes the curvature of spacetime in a form suitable for Einstein's field equations:

$$G_{\mu\nu} = 8\pi G T_{\mu\nu} \tag{2}$$

where

- G is the Newtonian's gravitational constant?
- $T_{\mu\nu}$ is the stress-energy tensor, describing the distribution and flow of energy and matter.

Despite its profound success in describing gravitational phenomena at macroscopic scales, General Relativity does not account for the microscopic origins of gravity. This limitation has led to the development of emergent-gravity theories, which propose that gravity arises as a collective effect stemming from fundamental microscopic processes. Additionally, quantum mechanics indicates that all known physical phenomena originate from interactions among elementary particles, suggesting that gravity may also be an emergent phenomenon rooted in microscopic interactions. In this context, this work explores the hypothesis that residual microscopic interactions—such as those involving particle spin, electromagnetic binding, strong nuclear confinement, weak interactions, and quantum vacuum fluctuations—collectively contribute to an effective gravitational effect manifested through spacetime curvature.

1.2 Emergent Gravity

Emergent gravity theories propose that gravity is not fundamental but arises from collective microscopic behavior. Examples include:

i. Thermodynamic gravity (Jacobson, 1995)

ii. Entropic gravity (Verlinde, 2011)

iii. Holographic gravity and

iv. Quantum information approaches.

These theories suggest that spacetime geometry may emerge from microscopic structures in a manner analogous to thermodynamic laws emerging from molecular dynamics.

However, most existing models focus on entropy and quantum information. The possible role of microscopic interaction forces, particle spin, binding energies, and vacuum effects remains less developed.

1.3. Objective

The objective of this work is to formulate a mathematical framework in which residual microscopic interactions produce spacetime curvature through an emergent scalar field.

The study specifically seeks to establish the chain

2. Mathematical Preliminaries

2.1 Spacetime Geometry

Let $(M, g_{\mu\nu})$ be a four-dimensional Lorentzian spacetime manifold, where $g_{\mu\nu}$ is the metric tensor.

The metric determines:

i. distances,

ii. angles,

iii. causal structure and

iv. spacetime geometry.

2.2. Residual Interaction Field

Let $F_R(x)$ denote the residual microscopic interaction density arising from the collective contributions of

$F_{em}, F_s, F_w, F_{spin}, F_{vac}$, namely,

$$F_R = F_{em} + F_s + F_w + F_{spin} + F_{vac}. \quad (3)$$

This field represents the net microscopic interaction proposed to generate emergent gravity.

2.3. Emergent Scalar Field

It is postulated that the residual interactions generate a macroscopic scalar field Φ.

Mathematically,

$$\Phi = \Phi(F_R). \quad (4)$$

Thus,

$$F_R \longrightarrow \Phi. \quad (5)$$

2.3. Einstein Tensor

The Einstein tensor is

$$G_{\mu\nu} = R_{\mu\nu} - \frac{1}{2} R g_{\mu\nu}, \quad (6)$$

Where

- $R_{\mu\nu}$ is the Ricci curvature tensor and
- $R = g^{\mu\nu} R_{\mu\nu}$ is the Ricci scalar.

The Einstein tensor completely characterizes spacetime curvature.

2.4. Stress-Energy Tensor

The stress-energy tensor measures:

i. energy density,

ii. momentum density,

iii. pressure and

iv. stresses.

For ordinary matter (m), stress-energy tensor is given as:

$$T_{\mu\nu}^{m}(m). \tag{7}$$

For the scalar field (Φ) , it is given as:

$$T_{\mu\nu}^{(\Phi)}. \tag{8}$$

2.5. Variational Formulation

Total Action

The total action is

$$S = S_{grav} + S_{\Phi} + S_m, \tag{9}$$

3.0. Main Theorem

3.1. Theorem 1: Residual Microscopic Interactions Generate Spacetime Curvature

3.2. Statement:

Let $F_R(x)$denote a residual microscopic interaction field generated by the collective effects of particle spin, electromagnetic binding, strong nuclear confinement, weak interactions, and quantum vacuum fluctuations.
Suppose there exists a differentiable scalar field:

$$\Phi = \Phi(F_R), \tag{10}$$

induced by the residual interaction field. Then the energy and momentum carried by (Φ) contribute to the Einstein field equations and consequently generate spacetime curvature.

3.3. Proof

3.3.1. Construct the Total Action

Considering the Einstein-Hilbert action coupled to the scalar field,

The total action is

$$S = S_{grav} + S_{\Phi} + S_m,$$

Where

$$S_{grav} = \frac{1}{16\pi G} \int_M R\sqrt{-g}\, d^4x, \tag{11}$$

$$S_m = \int_M \mathcal{L}_m \sqrt{-g}\, d^4x, \tag{12}$$

And

$$S_\Phi = \int_M \left[-\frac{1}{2}\nabla_\mu \Phi \nabla^\mu \Phi - V(\Phi)\right]\sqrt{-g}\, d^4x. \tag{13}$$

Meaning of the Terms

$\boldsymbol{G}$ Newton's gravitational constant.

$\boldsymbol{R}$ Ricci scalar curvature.

$\sqrt{-\boldsymbol{g}}$ Invariant spacetime volume element.

$\boldsymbol{V(\Phi)}$ Potential energy of the scalar field.

$\boldsymbol{\nabla_\mu}$ Covariant derivative.

3.3.2. Apply Hamilton's Principle

Hamilton's principle states that physical solutions satisfy:

$$\delta S = 0. \tag{14}$$

Varying the action with respect to the metric tensor, $g_{\mu\nu}$.

Thus,

$$\delta S = \delta S_{grav} + \delta S_\Phi + \delta S_m. \tag{15}$$

3.3.3. Variation of the Einstein-Hilbert Action

A fundamental theorem of General Relativity gives:

$$\delta S_{grav} = \frac{1}{16\pi G}\int_M G_{\mu\nu}\delta g^{\mu\nu}\sqrt{-g}\, d^4x. \tag{16}$$

This result follows from the variation of the Ricci scalar.

Hence the Einstein tensor naturally emerges from the variational principle.

3.3.4. Variation of the Matter Action

The stress-energy tensor is defined by:

$$T_{\mu\nu} = -\frac{2}{\sqrt{-g}}\frac{\delta S_m}{\delta g^{\mu\nu}}. \tag{17}$$

Therefore,

$$\delta S_m = -\frac{1}{2}\int_M T^{(m)}_{\mu\nu}\delta g^{\mu\nu}\sqrt{-g}d^4x. \tag{18}$$

3.3.5. Variation of the Scalar Field Action

Similarly,

$$\delta S_{\Phi} = -\frac{1}{2}\int_{M} T_{\mu\nu}^{(\Phi)}\ \delta g^{\mu\nu}\sqrt{-g}\, d^4x. \tag{19}$$

The scalar-field stress-energy tensor is:

$$T_{\mu\nu}^{(\Phi)} = \nabla_{\mu}\Phi\nabla_{\nu}\Phi - g_{\mu\nu}[\frac{1}{2}\nabla_{\alpha}\Phi\nabla^{\alpha}\Phi + V(\Phi)]. \tag{20}$$

Interpretation of the Scalar Stress-Energy Tensor

The first term;

$$\nabla_{\mu}\Phi\nabla_{\nu}\Phi, \tag{21}$$

represents the kinetic energy contribution.

The second term;

$$\frac{1}{2}\nabla_{\alpha}\Phi\nabla^{\alpha}\Phi + V(\Phi). \tag{22}$$

represents:

i. potential energy,
ii. pressure and
iii. isotropic stress.

Thus the scalar field carries energy and momentum.

3.3.6. Combine All Variations

Substituting into

$$\delta S = 0,$$

gives:

$$\frac{1}{16\pi G}\int_{M} G_{\mu\nu}\delta g^{\mu\nu}\sqrt{-g}\, d^4x - \frac{1}{2}\int_{M} T_{\mu\nu}^{(m)}\delta g^{\mu\nu}\sqrt{-g}d^4x - \frac{1}{2}\int_{M} T_{\mu\nu}^{(\Phi)}\ \delta g^{\mu\nu}\sqrt{-g}\, d^4x = 0. \tag{23}$$

This reduces to

$$\left(G_{\mu\nu}\delta g^{\mu\nu}\sqrt{-g}\right)\frac{1}{16\pi G}\int_M d^4x\ -\frac{1}{2}T_{\mu\nu}^{(m)}\delta g^{\mu\nu}\sqrt{-g}-T_{\mu\nu}^{(\Phi)}\delta g^{\mu\nu}\sqrt{-g}\int_M d^4x=0. \tag{24}$$

$$\therefore\left[\frac{G_{\mu\nu}}{16\pi G}-\frac{1}{2}T_{\mu\nu}^{(m)}-\frac{1}{2}T_{\mu\nu}^{(\Phi)}\right]\int_M d^4x=0. \tag{25}$$

$$\Rightarrow\left[\frac{G_{\mu\nu}}{16\pi G}-\frac{1}{2}T_{\mu\nu}^{(m)}-\frac{1}{2}T_{\mu\nu}^{(\Phi)}\right]=0\ \ or\ \ \int_M d^4x=0. \tag{26}$$

But

$$\int_M d^4x\neq\ 0. \tag{27}$$

Hence,

$$\left[\frac{G_{\mu\nu}}{16\pi G}-\frac{1}{2}T_{\mu\nu}^{(m)}-\frac{1}{2}T_{\mu\nu}^{(\Phi)}\right]=0. \tag{28}$$

$$\therefore G_{\mu\nu}=8\pi G\left[T_{\mu\nu}^{(matter)}+T_{\mu\nu}^{(\Phi)}\right] \tag{29}$$

Now, (29) is the **modified Einstein field equation**.

3.3.7. Connect Residual Interactions to Curvature

By hypothesis,

$$\Phi=\Phi(F_R). \tag{30}$$

Therefore,

$$T_{\mu\nu}^{(\Phi)}=T_{\mu\nu}^{(\Phi(\mathrm{F_R}))}. \tag{31}$$

Hence,

$$F_R\longrightarrow\Phi\longrightarrow T_{\mu\nu}^{(\Phi)}\longrightarrow G_{\mu\nu}. \tag{32}$$

This chain shows that residual interactions influence spacetime curvature through the scalar field.

3.3.8. Demonstrate Curvature Generation

Supposing

$$F_R\neq 0. \tag{33}$$

Then

$$\Phi \neq 0. \tag{34}$$

Consequently,

$$\nabla_\mu \Phi \neq 0, \tag{35}$$

Or

$$V(\Phi) \neq 0. \tag{36}$$

Therefore,

$$T_{\mu\nu}^{(\Phi)} \neq 0. \tag{37}$$

Einstein's equations then imply;

$$G_{\mu\nu} = 8\pi G\left[T_{\mu\nu}^{(matter)} + T_{\mu\nu}^{(\Phi)}\right] \neq 0. \tag{38}$$

Hence,

$$G_{\mu\nu} \neq 0. \tag{39}$$

But, (39) means spacetime is curved.

Therefore, the residual interactions generate curvature.

Q.E.D.

4.0. Conclusion

Starting from the Einstein-Hilbert variational principle, it is demonstrated herein that:

1. Residual microscopic interactions produce a scalar field
$$F_R \rightarrow \Phi.$$
2. The scalar field possesses a stress-energy tensor
$$T_{\mu\nu}^{(\Phi)}.$$
3. This tensor enters Einstein's field equations
$$G_{\mu\nu} = 8\pi G\left[T_{\mu\nu}^{(matter)} + T_{\mu\nu}^{(\Phi)}\right].$$
4. Nonzero residual interactions imply nonzero curvature.

Therefore, Residual microscopic interactions induce effective spacetime curvature.

References

1. Einstein A, (1916). *The foundation of the general theory of relativity*. *Annalen der Physik, 49*(7), 769–822. https://doi.org/10.1002/andp.19163540702
2. Jacobson T. (1995). Thermodynamics of spacetime: The Einstein equation of state. *Physical Review Letters, 75*(7), 1260–1263. https://doi.org/10.1103/PhysRevLett.75.1260
3. Verlinde E. (2011). On the origin of gravity and the laws of Newton. *Journal of High Energy Physics, 2011*(4), 29. https://doi.org/10.1007/JHEP04(2011)029

Establish the prevalence of clinical depression among secondary school adolescents in Murang'a East Sub-County in Kenya.

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Abstract

Prevalence of clinical depression among adolescents varies across geographical, cultural, and socioeconomic contexts. According to the World Health Organization, depression is a leading cause of disability worldwide, including among school-going adolescents. This study sought to determine the prevalence of clinical depression among secondary school adolescents in Murang'a East Sub-County, Kenya. A cross-sectional correlational research design was employed, targeting 369 students aged 14–18 years from three purposively selected mixed-gender schools (rural, peri-urban, and urban). Of the 369 sampled students, 363 successfully completed the questionnaires. Participants were stratified by class levels (form two and three), and by gender within each stratum. Stratified simple random sampling was applied within each stratum to ensure gender proportionality. Data was collected using the Beck Depression Inventory-II (BDI-II), which classifies depressive symptoms into subthreshold, mild, moderate, and severe categories. 31.4% had subthreshold depression, 21.2% mild, 28.7% moderate, and 18.7% severe depression. Subthreshold depression emerged as the most prevalent, indicating significant emotional distress even among those not meeting the clinical threshold. Moderate and severe depression, accounting for nearly half the sample, signaled an urgent need for mental health intervention, that if undressed can potentially impact academic performance, and overall well-being. High prevalence of clinical depression among adolescents in Murang'a East Sub-County underscore the necessity for a comprehensive tiered mental health support system in schools, that includes preventive measures such as, creating awareness, early screening and psychoeducation, to professional interventions for those with acute symptoms. Schools are uniquely positioned as frontline institutions for identifying and addressing adolescent mental health challenges, hence the need to be strengthened to enhance this role.

Background

Prevalence of clinical depression among secondary school adolescents is a growing global concern. Studies indicate a notable rise in depression rates, particularly among girls. Daly[1] found a 7.7% increase in U.S. adolescent depression over a decade, with girls experiencing a dramatic surge. Similarly, a study conducted by Saluja et al.[2] in the US observed that girls were more prone to depressive symptoms than boys, with the prevalence increasing with age. These findings point to a gender disparity in adolescent mental health and call for gender-sensitive approaches in prevention and intervention strategies in schools.

Elsewhere, Shorey et al.[3] identified a global prevalence of 34% for self-reported elevated depressive symptoms among 10–19-year-olds, with regions like Africa and Asia showing higher rates. Bhattarai et al. [4] in Nepal reported that 44.2% of adolescents reported depression symptoms, linked to low social support and low self-esteem. Similarly, Nirudya et al.[5] in India reported that a 37% depression prevalence. These studies highlight the widespread nature of adolescent depression and underscore the need for psychosocial support systems.

In Sub-Saharan Africa, depression among adolescents is influenced by structural and socio-demographic factors. Thus Sequeira et al.[6] noted limited mental health services and poor policy integration across SSA. In yet another study Nzeadibe et al.[7] found urban South African adolescents were more depressed than rural peers, with factors such as income, age, and race contributing. Oderinde et al.[8] in Nigeria linked depression to maternal death, low socioeconomic status, and exposure to violence. These findings stress the need for tailored interventions and policy frameworks sensitive to local context and adversity.

Studies conducted in East Africa show high levels of adolescent depression. Thus Girma et al.[9] reported that 28% prevalence in Ethiopia, linked to adverse childhood experiences and low social support. In Rwanda, Mukantwali et al.[10] reported that 51% of high school students experienced depression. In Uganda, Nsereko et al.[11] reported that 26.6% of adolescents had clinical depressive symptoms, with girls and those living with one or no parent being particularly vulnerable. These patterns reflect shared risk factors across the region, including poverty, violence, and weak support systems.

Kenyan studies also reflect significant adolescent mental health concerns. Studies by Osborn et al.[12] reported that more than 42% of youths had elevated depression symptoms. Studies in Kakamega and Makueni reported depression rates of 45% and 58.9% respectively, with age and gender being key risk factors.[13,14] Nyayieka et al.[15] linked depression to academic performance, while Mbwayo et al.[16] highlighted teachers' struggles in managing mental health in schools. Elsewhere, Kamau et al.[17] emphasized delayed access to care. On the whole, these findings call for urgent school-based and policy-level responses to adolescent mental health in Kenya.

Adolescent females are generally more prone to depression than their male counterparts, due to factors, such as hormonal changes, societal expectations, and gender-related stressors[11] Depression in this age group is frequently undiagnosed and comorbid with other mental or behavioral disorders. Parenting environment, family history of mental illness, exposure to trauma, bullying, academic pressure, and substance use have been implicated as risk factors[18] Understanding these determinants is crucial for developing targeted interventions and improving adolescent mental health outcomes

Objective

The main objective of this research was to determine the prevalence of clinical depression among secondary school adolescents in Murang'a East Sub-County, Kenya. By identifying how widespread clinical depression is within this population, the study aimed to shed light on the extent of the mental health burden affecting adolescents in the county. Result of the study, provide valuable insights that could guide development of targeted mental health interventions, enhance mental health support systems in schools, and influence policy decisions aimed at promoting adolescent well-being.

Methodology

This study adopted a cross-sectional correlational research design to explore the relationship between perceived parenting styles and clinical depression among adolescents in Murang'a East sub-County, Kenya. A total of 363 students, drawn from 33 schools, from three mixed-gender secondary schools, from rural, peri-urban, and urban settings, successfully completed questionnaires. Participants were aged between 14-18 years. The school were purposively selected, with sample allocation done in proportion to school enrollment. Participants were stratified

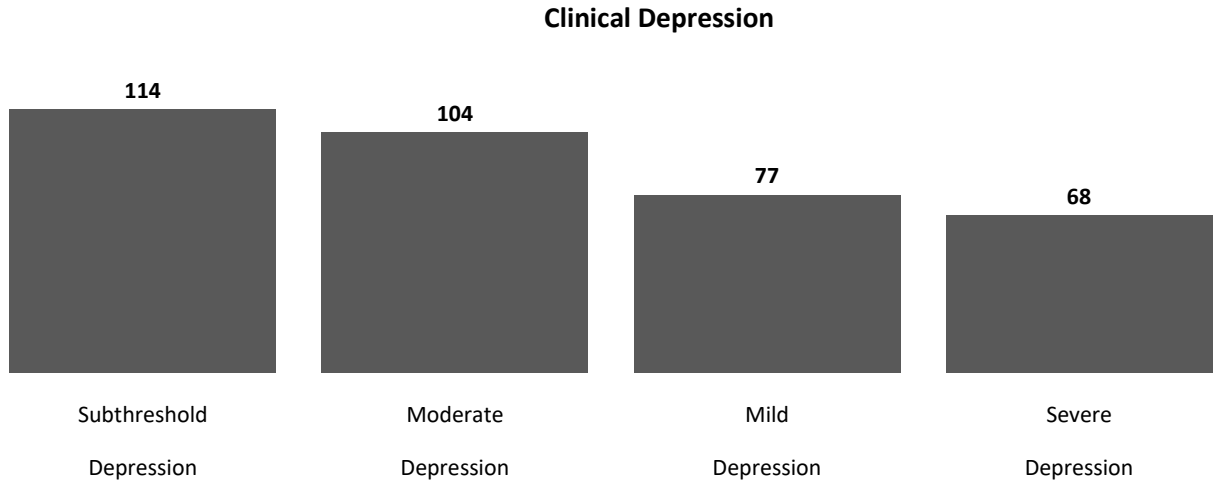
by class levels (form two and three), and by gender within each stratum. Stratified simple random sampling within each stratum ensured gender proportionality. Data was collected using the Beck Depression Inventory-II (BDI-II) to measure presence and severity depressive symptoms. In addition to this standardized instrument, a demographic section was incorporated into the questionnaire to capture data on gender, class level, family structure and family social economic status.

Results

The table below presents descriptive findings on prevalence of clinical depression using BDI-II. Based on standard cut off scores 0–13 (no depression), 14–19 (mild depression), 20–28 (moderate depression), and 29–63 (severe depression), students were classified into four main categories of depression severity: subthreshold, mild, moderate, and severe.

Figure 1

Descriptive Findings for clinical depression prevalence



Results revealed varying levels of depressive symptoms across the four BDI-II categories. Specifically, 114 (31.4%) students presented with subthreshold depression, 77 (21.2%) mild depression, 104 (28.7%) moderate depression, and 68 (18.7%) severe depression. These findings indicate that more than half of the respondents were experiencing varying levels of emotional and psychological distress, ranging from early-stage symptoms to clinically significant depressive disorder.

Subthreshold depression emerged as the most prevalent form of depressive symptomatology, reported by 114 (31.4%) students. Although these students scored below the clinical threshold (cut-off score of 14), their responses suggested presence of notable distress that does not meet the full criteria for a depressive disorder. Subthreshold symptoms such as low mood, irritability, and reduced motivation may appear subtle but are clinically important, as they are associated with a heightened risk of developing major depression later in life. High prevalence of subthreshold depression highlights the need for preventive mental health strategies, including early identification, regular emotional well-being assessments, and low-intensity interventions in school settings.

Moderate depression, was reported by 104 of 363(28.6%) students, representing the second most common category. These students scored between 20 and 28 on the BDI-II, indicating persistent and clinically significant depressive symptoms. Adolescents in this group are likely to experience considerable functional impairment, including poor academic performance, difficulty maintaining peer relationships, and a decline in daily motivation. Presence of moderate depression in nearly one-third of the sample underscores the urgent need for school-based psychological support services and access to professional mental health care when necessary. Schools should prioritize the development of internal support structures such as counseling units, mental health clubs, and trained staff to address students' emotional needs.

Mild depression was reported by 77 of 363 (21.2%) students, whose scores ranged from 14 to 19. Although less intense than moderate or severe depression, mild depression still carries the potential to disrupt learning, concentration, and emotional regulation. Students in this category may benefit from early interventions such as guided peer support, psychoeducation, and mental health awareness programs. Importantly, mild depression presents a critical opportunity for intervention before symptoms intensify.

Finally, 68 of 363 (18.7%) students reported severe depression, scoring between 29 and 63. These students are at the highest risk and may present with symptoms such as hopelessness, social withdrawal, and suicidal ideation. Presence of severe depression in this population necessitates immediate professional assessment, crisis intervention mechanisms, and collaboration with families and health professionals to safeguard the students' welfare.

Conclusion

It is concluded that clinical depression is highly prevalent among adolescents in Murang'a East sub-County, with a substantial number of students experiencing moderate to severe symptoms. These levels of depression, if left unaddressed, may impair academic performance, social relationships, and negatively impact psychological well-being. The distribution of depression severity underscores the need for tiered interventions ranging from preventative mental health education for students, to targeted psychological support for those with more acute symptoms.

Results of this study affirm that schools are strategically positioned to serve as the first line of detection and support in addressing adolescent mental health issues. Therefore, integrating mental health into the broader school health framework is not only necessary but urgent.

Recommendations

The Ministry of Education, in partnership with the Ministry of Health, should design and implement structured school-based mental health programs, that focus on awareness education, emotional wellness promotion, and student led programs such as, mental health clubs, peer support programs, and regular mental wellness activities.

Equally important is the capacity-building of teachers and school counselors through mental health training to enable early identification of depressive symptoms and timely referral for professional help. Parental and community engagement should also be prioritized through sensitization campaigns aimed at reducing stigma and fostering supportive home environments.

At the policy level, the Ministry of Education and other relevant stakeholders should embed adolescent mental health into the national school health framework. This requires formulation and enforcement of clear guidelines to support school-based mental health promotion and responsive strategies.

References

1. Daly M. Prevalence of depression among adolescents in the U.S. from 2009 to 2019: Analysis of trends by sex, race/ethnicity, and income. J Adolesc Health. 2022;70(3):496–9.
2. Saluja G, Iachan R, Scheidt PC, Overpeck MD, Sun W, Giedd JN. Prevalence of and risk factors for depressive symptoms among young adolescents. Arch Pediatr Adolesc Med. 2024;158(8):760–5. https://doi.org/10.1001/archpedi.158.8.760
3. Shorey S, Ng ED, Wong HJ. Global prevalence of depression and elevated depressive symptoms among adolescents: A systematic review and meta-analysis. Br J Clin Psychol. 2022;61(2):287–305.
4. Bhattarai D, Shrestha N, Paudel S. Prevalence and factors associated with depression among higher secondary school adolescents of Pokhara Metropolitan, Nepal: A cross-sectional study. BMJ Open. 2020;10: e044042. https://doi.org/10.1136/bmjopen-2020-044042
5. Nirudya V, Mohan MR, Chandrasekhar RS, Purushotham A, Mano VR. Prevalence of depression in school-going adolescents and its impact on scholastic performance: A cross-sectional study. Cureus. 2023;15(4): e38340. https://doi.org/10.7759/cureus.38340
6. Sequeira M, Singh S, Fernandes L, Gaikwad L, Gupta D, Chibanda D, Nadkarni A. The status of adolescent mental health research, practice and policy in sub-Saharan Africa: A narrative review. Trop Med Int Health. 2022;27(9):758–66.
7. Nzeadibe CT, Igboeli EE, Ajaero CK. Rural-urban differences in the prevalence and predictors of depression among adolescents in South Africa. S Afr J Child Health. 2018;2018(1): s71–s74
8. Oderinde K, Dada M, Ogun O, Awunor N, Kundi B, Ahmed H, et al. Prevalence and predictors of depression among adolescents in Ido Ekiti, South West Nigeria. Int J Clin Med. 2018; 9:187–202. https://doi.org/10.4236/ijcm.2018.93017
9. Girma S, Tsehay M, Mamaru A, Abera M. Depression and its determinants among adolescents in Jimma town, Southwest Ethiopia. PLOS ONE. 2021;16(5): e0250927. https://doi.org/10.1371/journal.pone.0250927
10. Mukantwali M, Bugenimana A, Kanyamanza C, Mutabaruka J, Niyonsenga J. Prevalence of depression, anxiety and stress and their risk and protective factors among secondary students in Rwanda during the first wave of COVID-19 pandemic. PLOS ONE. 2023;19(7): e0306389. https://doi.org/10.1371/journal.pone.0306389
11. Nsereko JR, Garman EC, Roomaney R. Depressive symptoms and socio-demographic correlates among adolescents in Kampala: A cross-sectional study. S Afr J Psychol. 2022;52(3):313–24.
12. Osborn TL, Venturo-Conerly KE, Gan JY, Rodriguez M, Alemu RG, Roe E, et al. Depression and anxiety symptoms amongst Kenyan adolescents: Psychometric properties, prevalence rates and associations with

psychosocial wellbeing and sociodemographic factors. Res Child Adolesc Psychopathol. 2022;50(11):1471–85.

13. Bakesia G, Olayo R, Mengich G, Opiyo R. Prevalence and sociodemographic predictors of depression among adolescents in secondary schools in Kakamega County, Kenya. East Afr Med J. 2023;100(8). https://www.ajol.info/index.php/eamj/article/view/258011
14. Mucherah W. Prevalence of depression among adolescents in selected public secondary schools in Makueni County, Kenya. Afr J Clin Psychol. 2022;4(3).
15. Nyayieka MA, Nyagwencha SK, Nzyuko S. Correlation of clinical depression, anxiety and academic performance of adolescents in selected secondary schools in Kenya. Am J Appl Psychol. 2020;9(1):14–21.
16. Mbwayo AW, Mathai M, Khasakhala LI, Kuria MW, Vander Stoep A. Mental health in Kenyan schools: Teachers' perspectives. Glob Soc Welf. 2020; 7:155–63.
17. Kamau JW, Omigbodun OO, Bella-Awusah T, Adedokun B. Who seeks child and adolescent mental health care in Kenya? A descriptive clinic profile at a tertiary referral facility. Child Adolesc Psychiatry Ment Health. 2017;14(11):14. https://doi.org/10.1186/s13034-017-0151-x
18. Delvecchio E, Germani A, Raspa V, Lis A, Mazzeschi C. Parenting styles and child's well-being: The mediating role of the perceived parental stress. Eur J Psychol. 2020;16(3):514–31.

DIGITAL INFORMATION LITERACY AND UTILIZATION OF ELECTRONIC RESOURCES AMONG LIBRARY USERS AT LAIKIPIA UNIVERSITY, KENYA

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Abstract

Electronic resources have become essential to postgraduate teaching, learning and research, but their academic value depends on users' ability to identify, search, evaluate and apply digital information effectively. This article examined digital information literacy and utilization of electronic resources among library users at Laikipia University, Kenya. The study adopted a mixed-methods case study design. Questionnaires were administered to 142 postgraduate students, of whom 140 responded, while interviews were conducted with all three senior librarians, producing an overall response rate of 98.6%. Quantitative data was analyzed using frequencies and percentages, and qualitative interview data was analyzed thematically. The findings showed that digital information literacy was moderate. More than half of the students (53.7%) had not received formal library training on electronic resources. Although 51.5% were confident or very confident in searching for scholarly materials, only 40.7% were confident or very confident in evaluating the relevance and credibility of retrieved information; 44.3% were slightly confident or not confident at all. Nevertheless, electronic resources were central to postgraduate work: 57.1% reported that they supported dissertations, theses, coursework and academic writing to a great or very great extent, while 66.4% used them often or very often for research and academic writing. Librarians confirmed that training, awareness, lecturer recommendations and search competence strongly shaped utilization. Major constraints included poor internet connectivity, authentication problems, limited awareness, complex platforms and inadequate digital literacy skills. It is concluded that access alone does not ensure effective use. There is need for Laikipia University to institutionalize continuous, research-oriented digital information literacy training, strengthen remote access and internet infrastructure, simplify platforms and expand proactive user support.

Keywords: Digital Information Literacy, Electronic Resources, Postgraduate Students, Academic Libraries, Laikipia University.

Introduction

Academic libraries have undergone a major transition from predominantly print-based collections to hybrid and digital information environments. This change has expanded access to scholarly journals, databases, electronic books, institutional repositories and open access materials, enabling university students and researchers to obtain current information beyond the physical library [1]. In African universities, however, availability of electronic resources has not always translated into their full academic use because infrastructure, user competence, awareness, funding

and access systems remain uneven [2]. Kenyan universities have similarly invested in electronic collections in response to national standards that require university libraries to provide adequate, current and accessible information resources for teaching, learning and research [3].

Digital information literacy is therefore central to the value of electronic resource investments. It refers to the ability to recognize an information need, identify suitable electronic sources, design and execute effective searches, evaluate relevance and credibility of retrieved information, manage information ethically and use it appropriately in academic work [4]. The concept extends beyond basic computer operation. Thus, a student may know how to open a browser or access a database but still lack the competence to select appropriate keywords, use Boolean operators, distinguish peer-reviewed evidence from unreliable content, evaluate authorship and publication quality, or cite digital sources correctly. Academic libraries play a critical educational role by providing orientations, workshops, research consultations and embedded instruction that develop these abilities [5].

Previous research has consistently linked information literacy with use of electronic resources. Students who can clearly define their information needs, formulate search strategies and evaluate sources are more likely to retrieve relevant scholarly material and integrate it into assignments and research [6]. Conversely, limited search and evaluation skills may lead to information overload, Studies conducted in Kenya have demonstrated that postgraduate students continue to experience challenges in information retrieval, source evaluation and citation despite institutional investments in digital resources and user education [7,8]. Low awareness and infrequent training have also been identified as reasons why some postgraduate users rarely use subscribed resources [9].

Laikipia University Library provides access to a range of electronic resources through institutional subscriptions, consortium arrangements, her institutional repository and open access sources. The university is located in a predominantly rural setting, making it an important context for understanding how digital competence interacts with infrastructure, remote access and institutional support. This article draws from a wider study on collection development and e-resource utilization and focuses specifically on the level of digital information literacy among postgraduate library users and how that level shapes effective utilization of electronic resources.

University libraries incur substantial costs acquiring, licensing and maintaining electronic information resources yet these investments yield academic value only when intended users are aware of the resources and possess the skills required to access, search, evaluate and apply them. Notably however, electronic resource utilization in Kenyan Universities is constrained by inadequate digital literacy, limited awareness, poor connectivity, complex platforms and authentication difficulties [8,10]. These challenges can result in a gap between resource availability and

actual use, weaken the return on institutional investment and limit students' access to authoritative scholarly evidence.

At Laikipia University, there was limited empirical evidence showing whether postgraduate students possessed the digital information literacy competencies required to use the university's electronic collections effectively. It was also unclear whether students who received library training considered it useful, how confident they were in searching and evaluating information, and the extent to which e-resources supported their research and academic writing. Addressing this gap was necessary for designing user education and support services that move beyond mere access toward meaningful, critical and sustained utilization. Effective utilization includes awareness of available resources, successful authentication, identification of relevant platforms, purposeful searching, retrieval of full text, critical evaluation and integration of evidence into academic outputs. Research in African universities shows that the use of e-resources is often reduced by unstable internet, lack of training, limited awareness and insufficient technical support [10,12]. In Kenya, university libraries have expanded subscriptions and information services, but the practical value of these resources remains dependent on access conditions and user preparedness [13]. With the view to supporting research in Kenyan Universities, there is need for a deliberate study to determine the level of digital acquisition and literacy support offered to Kenyan researchers by University libraries.

Objective of the Study

The study sought to evaluate the level of digital information literacy among library users at Laikipia University and examine its influence on effective utilization of electronic resources.

Theoretical Perspective

The study was informed primarily by the SCONUL Seven Pillars of Information Literacy and the Technology Acceptance Model. The SCONUL framework conceptualizes information literacy as a continuing cycle of identifying an information need, scoping existing knowledge, planning a search, gathering information, evaluating it, managing it and presenting or applying it [14]. These pillars provided a basis for interpreting students' confidence in searching and evaluating scholarly information. The Technology Acceptance Model proposes that the adoption of a technology is shaped by perceived usefulness and perceived ease of use [15]. It was relevant because students' willingness to use electronic resources depends partly on whether the platforms support academic work and whether access and navigation are manageable. Together, the two perspectives connect user capability with perceptions of the digital systems through which information is delivered.

Methodology

The study adopted a mixed-methods case study design to provide both measurable patterns and deeper explanations of electronic resource use. The study was conducted at Laikipia University, a

Kenyan public university located approximately eleven kilometres from Nyahururu town. The institution was selected because its library provides subscribed databases, repository content and other electronic resources while serving users in a rural-based university context. Mixed methods were appropriate because questionnaire data could describe training, confidence and usage patterns, while interviews with librarians could explain how awareness, user support and institutional conditions influenced those patterns.

The target population comprised 220 postgraduate students and three senior librarians. The postgraduate sample was calculated using the Yamane formula at a five per cent margin of error, producing a target population of 142 students. Stratified random sampling was used for students, while the University Librarian, Systems Librarian and Reference Librarian were included because of their direct roles in electronic resource management and user support. A total of 140 student questionnaires were returned, and all three librarians participated in interviews.

Data was collected using a structured questionnaire and a semi-structured interview guide. The questionnaire measured training, perceived usefulness of training, confidence in searching, confidence in evaluating information, academic contribution of e-resources, frequency of use and barriers to utilization. The interview guide explored awareness, information literacy support, resource use and the role of lecturers and library staff. The instruments were piloted at Kirinyaga University to assess clarity, validity and reliability. Participation was voluntary, confidentiality and anonymity were protected, and the study followed institutional and national research authorization requirements.

Quantitative data was analyzed in IBM SPSS Version 28 using frequencies and percentages. Interview data was coded and analyzed thematically. Findings from the two data streams were integrated during interpretation. Since the source study reported descriptive rather than inferential statistics, the article interprets influence through converging response patterns and qualitative evidence; it does not claim a statistically estimated causal effect or correlation.

Results and Discussion

Response Rate and Respondent Profile

The study obtained 140 usable questionnaires from 142 postgraduate students and interviews from all three senior librarians. The overall response rate was 98.6%, providing an adequate basis for analysis. The student respondents included 98 Master students (70.0%) and 42 doctoral students (30.0%). 70 (50%) respondents were in their second year, while 47 (34.3%) were in the third year or beyond, indicating that most had sufficient exposure to the university's library services and research requirements.

Table 1: Response rate

Participant category	Targeted (n)	Actual responses (n)	Response rate (%)	Method
Postgraduate students	142	140	98.6	Questionnaire
Senior librarians	3	3	100.0	Interview
Total	145	143	98.6	Questionnaire/Interview

Level of Digital Information Literacy

Training coverage was limited. Seventy-five students (53.7%) reported that they had not received formal training from the library on the use of electronic resources, compared with 65 (46.3%) who had received training. This finding indicates that a slight majority were expected to navigate digital collections without structured library instruction. The result is important because database searching, information evaluation and ethical use are learned competencies that may not develop automatically through exposure to technology.

Among the respondents who answered the follow-up question on training usefulness (valid n = 62), 22 (35.5%) rated the training as very useful and 25 (40.3%) as useful. Therefore, 75.8% of valid respondents who had received training regarded it as useful or very useful. None described the training as not useful. The positive rating confirms the librarians' view that user education improves confidence and purposeful use. It also suggests that the main weakness was not the value of training but its reach and continuity.

Confidence in searching was moderate. A combined 72 respondents (51.5%) were confident or very confident in searching for scholarly materials, while 45 (32.1%) were moderately confident. Twenty-three (16.4%) were only slightly confident or not confident at all. Although these figures show that many students had workable search abilities, nearly half had not reached a strong level of confidence. This may limit the use of advanced database functions, subject-specific vocabulary and systematic search approaches.

Evaluation competence was weaker than search competence. Only 57 respondents (40.7%) were confident or very confident in evaluating the relevance and credibility of information obtained from electronic resources. By contrast, 49 (35.0%) were slightly confident and 13 (9.3%) were not confident at all. Combined, 44.3% had low evaluative confidence. This is a critical gap because the ability to retrieve information does not guarantee the ability to judge its authority, methodological quality, relevance or suitability for academic use. The pattern supports the argument that information literacy instruction should include critical evaluation, not only navigation and access [4,7].

Table 2: Digital information literacy indicators among postgraduate students

Indicator	Response category	Frequency (n)	Percentage (%)
Received formal library training	Yes	65	46.3
	No	75	53.7
Usefulness of training (valid n = 62)	Very useful	22	35.5
	Useful	25	40.3
	Moderately useful	8	12.9
	Slightly useful	7	11.3
	Not useful	0	0.0
Confidence in searching	Very confident	33	23.6
	Confident	39	27.9
	Moderately confident	45	32.1
	Slightly confident	20	14.3
	Not confident at all	3	2.1
Confidence in evaluating relevance and credibility	Very confident	27	19.3
	Confident	30	21.4
	Moderately confident	21	15.0
	Slightly confident	49	35.0
	Not confident at all	13	9.3

Utilization of Electronic Resources

Electronic resources were widely integrated in postgraduate academic work. Forty-nine students (35.0%) used them daily and 46 (32.9%) weekly. Thus, 67.9% used electronic resources at least weekly. None reported that they never used e-resources for general academic work, although 30 (21.4%) used them rarely. The high daily and weekly use demonstrates substantial demand for digital scholarly information, but the sizeable rarely-use group suggests that access and competence were not uniform.

When asked specifically about research and academic writing, 28 respondents (20.0%) used e-resources very often and 65 (46.4%) often. The combined proportion of 66.4% confirms that e-resources were central to postgraduate research practice. However, 22 students (15.7%) rarely or never used them for research and academic writing, indicating that a minority had not fully integrated library-provided digital resources into scholarly work.

The perceived academic contribution was also high. Thirty-eight students (27.1%) stated that electronic resources supported dissertations, theses, coursework or academic writing to a very great extent, and 42 (30.0%) to a great extent. A further 44 (31.4%) reported a moderate contribution. Overall, 88.5% experienced at least moderate academic support from e-resources. This finding reflects the perceived usefulness dimension of the Technology Acceptance Model, thus, students are more likely to use platforms that clearly contribute to research and academic performance [15].

Table 3: Utilization of electronic resources

Indicator	Response category	Frequency (n)	Percentage (%)
General frequency of use	Daily	49	35.0
	Weekly	46	32.9
	Monthly	15	10.7
	Rarely	30	21.4
	Never	0	0.0
Frequency for research and academic writing	Very often	28	20.0
	Often	65	46.4
	Sometimes	25	17.9
	Rarely	19	13.6
	Never	3	2.1
Extent of support to academic work	Very great extent	38	27.1
	Great extent	42	30.0
	Moderate extent	44	31.4
	Small extent	12	8.6
	Not at all	4	2.9

Influence of Digital Information Literacy on Utilization

The descriptive findings and interviews point to a clear practical influence of digital information literacy on utilization. First, students who had received training overwhelmingly judged it useful, while the librarians reported that trained students were more confident in searching databases and using retrieved materials. Second, search confidence was stronger than evaluation confidence, suggesting that many users could locate information but were less prepared to determine its scholarly quality. This difference matters because effective utilization requires both retrieval and critical appraisal. Third, the high frequency of e-resource use and strong perceived

academic contribution coexisted with moderate digital literacy. This indicates that postgraduate research requirements compel many students to use e-resources even when their skills are not fully developed. In such circumstances, use may be frequent but inefficient, limited to familiar platforms, dependent on lecturers or vulnerable to poor source selection. The librarians observed that students with low search skills could have access to resources yet fail to exploit them effectively. This observation aligns with studies showing that information need recognition, searching and evaluation are predictors of e-resource use [6,9]. In addition, lecturers and supervisors were important intermediaries, thus, in the broader study, 29.3% of students first learned about available resources through lecturers or supervisors, compared with 25.0% through library orientation. Interview participants explained that students were more likely to use databases and journals when supervisors recommended them or required scholarly sources in assignments and research. There is therefore need for digital literacy development to involve collaboration between librarians and academic departments, with instruction embedded in research methods, proposal development and postgraduate seminars.

Barriers Affecting Digital Literacy and Utilization

Digital literacy operated within significant infrastructural and systemic constraints. Poor or inconsistent internet connectivity was the most severe barrier, with 100 respondents (71.4%) reporting that it hindered use to a great or very great extent. Login and authentication problems affected 82 (58.6%) to the same degree. Limited awareness affected 76 (54.3%), complex platforms affected 72 (51.4%), irrelevant or outdated resources affected 65 (46.4%), and inadequate digital literacy skills affected 62 (44.2%).

These findings show why training alone cannot resolve underutilization. Thus, a student may possess good search skills but be prevented from accessing a database by unstable connectivity or authentication failure. Conversely, a stable platform may remain underused if students are unaware of it or cannot navigate its interface. The results support a combined intervention addressing competence, awareness, usability, infrastructure and resource relevance. Similar interactions between user skills and technical conditions have been reported in Kenyan and African universities [8,10,12].

Table 4: Major barriers to effective use of electronic resources

Barrier	Great or very great extent (n)	Combined percentage (%)
Poor or inconsistent internet connectivity	100	71.4
Login or authentication problems	82	58.6
Limited awareness of available e-resources	76	54.3

Barrier	Great or very great extent (n)	Combined percentage (%)
Complex platforms or navigation difficulties	72	51.4
Irrelevant or outdated resources	65	46.4
Inadequate digital literacy skills	62	44.2

Qualitative Insights from Librarians

The interview findings reinforced the quantitative patterns. Thus all three librarians emphasized that awareness and information literacy were major determinants of utilization. Students who attended training were perceived to be more confident in database searching, whereas students with limited awareness often did not know the full range of resources available. One librarian explained that students may have access to e-resources but still fail to use them effectively when they lack searching skills. Another noted that navigation was particularly difficult for users unfamiliar with the different interfaces used by database vendors.

The librarians also emphasized the influence of the academic environment. Notably, lecturer and supervisor recommendations encouraged students to use specific journals and databases, while departmental expectations concerning research and referencing increased purposeful use. E-resources were used most strongly when integrated into coursework, dissertation supervision and research tasks. These findings suggest that library training should not be separated from the curriculum; it should be delivered at points when students have immediate information needs.

In addition, continuous rather than one-off support was considered necessary. Librarians recommended repeated training, awareness creation, research assistance, prompt resolution of login problems, highlighted the need for stronger internet connectivity and reliable remote access because many postgraduate students conduct research away from the physical library. The qualitative evidence therefore confirms that effective utilization results from interaction of competent users, supportive academic staff, responsive librarians and reliable digital systems.

Strategies for Improvement

Respondents strongly supported interventions that address both human and technical dimensions. Improved internet connectivity received the highest support, with 78.6% agreeing or strongly agreeing that it would increase e-resource use. Acquisition of more relevant postgraduate resources was supported by 75.8%, simpler and more user-friendly platforms by 72.9%, more frequent training by 71.4%, increased awareness campaigns by 70.7%, and better library staff support by 69.3%. The pattern indicates that users do not view digital literacy as an isolated

individual responsibility but rather, expect institutional systems to make resources visible, relevant and accessible.

Table 5: Strategies supported by postgraduate students

Proposed strategy	Agree or strongly agree (n)	Combined percentage (%)
Improve internet connectivity	110	78.6
Acquire more relevant postgraduate resources	106	75.8
Provide simpler, user-friendly access platforms	102	72.9
Offer more frequent e-resource training	100	71.4
Increase library awareness campaigns	99	70.7
Strengthen support from library staff	97	69.3

Conclusion

It is concluded that digital information literacy among postgraduate library users at Laikipia University was moderate and materially shaped the effective use of electronic resources. Formal training had not reached a majority of students, yet those who received it generally considered it useful. Students displayed greater confidence in searching than in evaluating the credibility and relevance of information, revealing a particularly important weakness in critical information appraisal. Notably, electronic resources were widely used and made a substantial contribution to dissertations, theses, coursework and academic writing.

The findings demonstrate that resource availability is necessary but insufficient. Thus, meaningful utilization depends on awareness, search competence, critical evaluation, platform usability, reliable internet, functional authentication and responsive support. The convergence of questionnaire and interview evidence indicates that digital information literacy acts as a bridge between electronic resource provision and academic value. However, the bridge can function effectively only when supported by appropriate infrastructure and institutional collaboration.

Because the analysis was descriptive, the article does not quantify the strength of a statistical relationship between digital information literacy and utilization. Future research using individual-level composite scores and inferential analysis could estimate the relationship more precisely. Nevertheless, the present evidence provides a strong practical basis for improving user education and electronic resource services at Laikipia University.

Recommendations

1. There is need for Laikipia University Library to institutionalize continuous digital information literacy training for postgraduate students rather than relying mainly on entry-level orientation.

Training should be scheduled at proposal, literature review, data analysis and thesis-writing stages.

2. Training content should extend beyond basic database access to advanced search strategies, subject headings, Boolean operators, filters, systematic searching, critical evaluation of authorship and publication quality, citation management, ethical information use and responsible use of emerging AI tools.
3. The library should collaborate with lecturers, supervisors and departments to embed digital information literacy into research methods units, postgraduate seminars, coursework and supervision processes.
4. The university should improve internet bandwidth, authentication systems and seamless off-campus access so that students can apply their digital skills without recurrent technical interruption.
5. The library should simplify access pathways through a clear e-resource portal, subject guides, database tutorials and platform-specific quick guides, while providing prompt help for login and navigation problems.
6. Awareness campaigns should be conducted regularly through email alerts, the library website, learning management systems, departmental forums and targeted communication on newly acquired or underused resources.
7. Future studies should collect respondent-level digital literacy and utilization scores and apply correlation or regression analysis to determine the magnitude and statistical significance of the relationship.

References

1) Thanuskodi, S. (2021). *Trends and developments in library and information science research*. IGI Global. https://doi.org/10.4018/978-1-7998-5003-2

2) Ocholla, D. N., Ngulube, P., & Onyancha, O. B. (2020). Challenges and opportunities of electronic resources in African academic libraries. *Journal of Librarianship and Information Science, 52*(1), 1–13. https://doi.org/10.1177/0961000620949057

3) Commission for University Education. (2022). *Standards and guidelines for university libraries in Kenya*. Commission for University Education. https://www.cue.or.ke

4) Association of College and Research Libraries. (2016). *Framework for information literacy for higher education*. Association of College and Research Libraries. https://www.ala.org/acrl/standards/ilframework

5) Ari, R. (2023). Fostering information literacy through libraries in academic landscape. *International Journal of Research in Library Science, 9*(4), 1–8. https://www.ijrls.in

6) Kanori, J. (2025). *Influence of information literacy on utilization of electronic resources by Bachelor of Education teacher trainees, University of Nairobi, Kenya* (Master's thesis, University of Nairobi). University of Nairobi Repository. http://erepository.uonbi.ac.ke

7) Mwaki, G. K. (2023). *Information literacy skills and utilization of electronic information resources by postgraduate students in faith-based universities in Kenya* (Doctoral dissertation, University of Nairobi). University of Nairobi Repository. http://erepository.uonbi.ac.ke

8) Wamalwa, D. M., & Kiplangat, R. K. (2023). Challenges in accessing and utilizing information in digital resource platforms by academic staff in selected public universities in Kenya. *International Journal of Current Aspects, 7*(2), 65–80. https://doi.org/10.35942/ijcab.v7i2.314

9) Merande, A. K., Wamukoya, J., & Lutta, S. (2021). *Use of electronic information resources by postgraduate students in selected university libraries in Kenya*. University of Nairobi Institutional Repository. http://erepository.uonbi.ac.ke

10) Mwantimwa, K., Elia, E., & Mwanzini, M. S. (2022). Digital technologies and library services in higher education institutions: Preparedness and utilization. *University of Dar es Salaam Library Journal, 17*(1), 3–20. https://journals.udsm.ac.tz/index.php/lj/article/view/5421

11) Olatokun, W. M., & Akangbe, O. J. (2020). Use of electronic resources by postgraduate students in selected universities in South-West Nigeria. *Library Philosophy and Practice*, Article 3968. https://digitalcommons.unl.edu/libphilprac/3968/

12) Ubaga, E., & Kiarie, G. (2024). Re-engineering university library services with emerging technologies in Kenya: Prospects and challenges. *African Journal of Science, Technology and Engineering, 5*(1), 47–58.

13) Nyagah, D., Kemisa, S., & Ombongi, G. (2020). Assessment of information services provision in university libraries in accordance with the Commission for University Education guidelines: Selected university libraries in Western Kenya. *Library Philosophy and Practice*, Article 4614. https://digitalcommons.unl.edu/libphilprac/4614/

14) SCONUL Working Group on Information Literacy. (2011). *The SCONUL seven pillars of information literacy: Core model for higher education*. Society of College, National and University Libraries. https://www.sconul.ac.uk/page/seven-pillars-of-information-literacy

15) Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008