Journal: Texila Advanced Journal of Multidisciplinary Health Research
Publisher: Texila International Journal
ISSN: 3105-3564
Volume 5 Issue 2, 2025
DOI: 10.21522/TAJMHR.2016.05.02.Art030

The Scope of Infodemics in Cameroon: Misinformation, Digital Literacy and Determinants

Epie Kepche Gerard[1*], Tendongfor Nicholas[2], Anweh Vera Njang[3]
[1]*Texila American University/Universidad Central de Nicaragua*
[2]*Department of Public Health and Hygiene, Faculty of Health Sciences, University of Buea, Cameroon*
[3]*Department of Economics, Faculty of Social and Management Sciences, University of Buea, Cameroon*

Abstract

The COVID-19 pandemic and the Ebola outbreaks have demonstrated how infodemics and misinformation affect population health decision making, which in turn negatively affects public health interventions. Six regions of Cameroon were purposely selected to reflect the country's conflict dynamics as well as its cultural, linguistic and religious diversity. A total of 1439 participants 18 years and above were surveyed using a structured questionnaire. The analysis examined misinformation exposure across multiple health topics, digital literacy levels and behavior responses. Three composite indices were constructed: the Infodemic Exposure index, the Digital Literacy Index, and the Misinformation Behavior Index. Ordinary Least Squares (OLS) regression models identified key determinants of digital literacy and susceptibility to misinformation. The mean infodemic exposure score was 0.389, indicating moderate exposure to conflicting health information. Despite this, 70% of participants reported engaging in harmful health behavior due to misinformation. The digital literacy score was 0.397(0-1). Higher education, higher income and trust in official sources were positively associated with digital literacy, while living in rural areas, unemployment and peripheral information processing routes were negatively associated. Digital literacy was inversely associated with susceptibility to misinformation (β= - 0.052, $p<$ 0.050) and susceptibility to misinformation also predicted lower digital literacy (β= -0.078, $p<$ 0.050). These findings suggest that infodemic affects several health topics simultaneously out of crisis periods. Infodemic management and surveillance should be integrated into routine health systems. Strengthening digital literacy may support public health communication and interventions in Cameroon.

Keywords: *Cameroon, Digital Literacy, Infodemics, Misinformation*

Introduction

The topic of infodemics is gaining global recognition from international institutions, due to its harmful impact on our collective capacity to respond to health emergencies and promote health worldwide [1]. Although infodemics existed before, the COVID-19 pandemic marked the turning point, drawing global attention to their impact. The World Health Organization defines infodemics as an overabundance of information, both accurate and false, that makes it difficult for people to find reliable guidance during health crises[2]. Today, there is more evidence that infodemics and misinformation affect a wide range of public health areas, such as immunization

Received: 27.10.2025 ***Accepted: 17.11.2025*** ***Published on: 28.11.2025***
****Corresponding Author: gerardepie2981@gmail.com***

efforts, HIV/AIDS programs and non-communicable diseases management [1, 3].

In Cameroun, like in most African countries, the spread of misinformation has been reported in many health crises. This was seen during the COVID-19 pandemic and in the early years of HIV in Cameroon[4, 5]. In west Africa, misinformation had a negative impact during the Ebola outbreaks, where the health response teams were attacked, treatment centers were abandoned, and protective measures ignored by the population. Programs that are rooted in the community also faced challenges, like in northern Nigeria where polio vaccines were rejected by the population[6, 7]. The spread of misleading health information is aggravated with social media platforms like Facebook and WhatsApp that facilitate its spread. This is made worse when traditional sources, such as family and friends, religious leaders and community leaders, reinforce or relay unverified claims. The combined effect of online and offline channels makes it difficult for people to take informed decisions about their health [4, 8].

Studies in Cameroon have shown that misinformation affected people's decision during the COVID-19 pandemic. But these studies like others were focused on a single disease like COVID-19. No research has systematically examined how misinformation influences several health topics at the same time. This is important because the available evidence shows that there is a spillover effect from COVID 19 misinformation on routine vaccination [9]. In this context, understanding how people perceive infodemics and how they access and evaluate health information in their environment is important. Focusing on all health topic, rather than a single health topic, could point to ways to tackle this challenge holistically in low- and middle-income countries, especially Cameroon.

Health communication in response to public health events or health promotion in Cameroon and other African countries has relied on traditional communication campaigns, songs, SMS messaging, posters, radio spots, press releases and media monitoring [10, 11]. All these approaches facilitated information dissemination. In the context of infodemics, mostly due to online propagation of information, these approaches did not adequately mitigate the effects of misinformation on individual's health decision making during the COVID 19 pandemic. The inability of citizens to identify false content in the digital space, and the existing digital divide were not properly addressed. Digital literacy initiatives are limited and rarely target those who are vulnerable[12]. Moreso, most interventions react to misinformation rather than a continuous public health initiative.

WHO recommends integrating infodemic management into public health systems through 4 pillars: (1) information monitoring (infoveillance); (2) building eHealth Literacy and science literacy capacity; (3) encouraging knowledge refinement and quality improvement processes such as fact checking and peer-review; and (4) accurate and timely knowledge translation, minimizing distorting factors such as political or commercial influences[13]. This means that successful infodemics management will be achieved through reinforcing people's capacity to access, evaluate, comprehend, cross check and apply reliable health information. This will reduce misinformation vulnerability across diseases in a sustainable manner.

This study introduces 3 composite measures: (1) the infodemic exposure index, developed from the frequency of conflicting information and its emotional impact, (2) digital literacy index, capturing the ability in evaluating online content, and (3) the misinformation behavior index, captured from exposure to misinformation. This study aims to explore the link of infodemic exposure and digital literacy using primary data collected from a survey in 6 regions in Cameroon. Unlike single disease analyses, it considers a multiple health topic approach from vaccines, HIV/AIDS, malaria, maternal and child health, non-communicable diseases and COVID-19 to evaluate the nature and scope of infodemics across multiple health topics and the determinants of digital literacy and misinformation in Cameroon.

Materials and Methods

Description of the Site

This study was conducted across 6 regions of Cameroon: Centre, Littoral, North, North-west, South-west and West. These regions were selected considering the country's linguistic, cultural, religious and socioeconomic diversity. Urban and rural areas in each of these regions were also included in the study. This reflected the difference in access to information technologies, education and health services. The two anglophone regions experiencing a sociopolitical crisis [14] were included to document information flow in conflict settings. This context made it suitable for investigating how infodemics and misinformation propagate across multiple health domains and how they are influenced by sociodemographic characteristics.

Study Design and Population

We conducted a quantitative cross-sectional survey in six regions of Cameroon. We collected data from 1439 people aged 18 years and above.

Sampling and Recruitment

The questionnaire was shared using a stratified snowball sampling method, mimicking the natural flow and patterns of health information and misinformation within the social media space. WhatsApp was selected for the dissemination of the questionnaire, since it is the main source of health information propagation in Cameroon[4] and it serves as a digital gathering space for people having common interest in the form of WhatsApp groups. The research assistants in the 6 regions, initiated questionnaire distribution through purposely selected WhatsApp groups(seeds) representing diverse strata, including rural, urban, professional, sex and age based digital communities. Each region started with 11 seeds: 3 rural and 8 urban. Seed selection followed fixed criteria by age, sex, and profession. Each region's seeds included at least one WhatsApp group made up of young adults. Seeds covered both sexes and both formal and informal workers. The initial participants received the questionnaire via WhatsApp, and members were encouraged to fill and share it within their own networks and other WhatsApp groups. This allowed the sample to expand through peer-to-peer referrals, simulating the actual spread of health-related content and misinformation. This sampling method enabled the inclusion of diverse participants. Recruitment ran from May to June 2025. This method is non probabilistic, but it helped to observe and analyze how misinformation may influence health decisions across different social segments.

Questionnaire and Field Operations

A structured questionnaire covering demographics, digital access, exposure to health information, perceived misinformation, emotional overwhelm, information sources, and behavioral construct from the Health Believe Model (HBM) and the Elaboration Likelihood Model (ELM) were used. This questionnaire was available in French and English. Regional research assistants supported translation into local languages when needed and assisted offline respondents. We used KoboToolbox to generate the survey links. The electronic survey form had built-in controls to prevent partial submissions. A single-choice consent gate was at the start of the questionnaire. Selecting "No" ended the survey while still allowing a blank consent record. Participants were encouraged to submit once. A mandatory GPS-enabled question captured the geolocation of each submission, using the device's location services. Entries with identical GPS coordinates or duplicate identifiers were cross-checked, and duplicate submissions were removed.

Data Security and Ethics

Ethical approval was obtained from the Regional Ethics Committee for Human Health Research Southwest (CRERSH), Ref. No 56/CRERSH/SW/C/02/2025. Participants provided informed consent electronically before proceeding.

Data were stored on KoboToolbox servers with access restricted to the research team. Names of participants were not included in the analysis files.

Index Construction

To operationalize behavior and information patterns, three indices were constructed: Digital literacy index, infodemic exposure index and Misinformation behavior index.

Digital Literacy Index

The digital literacy index was predicted from the principal component analysis (PCA) and had both negative and positive values. These values were normalized to range 0 to 1. The primary indicators used to construct this index were: the confidence of the participants to search and crosscheck information using search engines; The confidence of the participant to identify reliable websites; the confidence of the participants to identify fake or engineered images and videos and Confidence of the participants to understand health information especially statistics. When normalized, a reduced indicator which has only positive values was obtained; where higher values indicate higher levels of digital literacy and lower values depict lower levels of digital literacy. The reduced indicator had values ranging from 0 to 1. It is worth indicating that 0.5 and above implies more digital literacy and below indicates less digital literacy.

Misinformation Behavior Index

The Misinformation Behavior Index was constructed using multiple correspondent analysis (MCA) because the primary indicators are binary in nature. The participants were asked if they had delayed or avoided care, skipped or delayed vaccination, adopted unproven remedies or distrusted an institution or campaign after hearing some health information that was later labelled as wrong or misinformation. The yes or no answers to these questions constituted the primary binary indicators used for constructing the index. The resulting factor scores were normalized between 0 and 1. Higher scores indicated stronger misinformation effect on behavior.

The formula for the composite index is presented as equation 1:

$$C_i = \frac{\sum_{k=1}^{K} \sum_{jk=1}^{JK} W_{jk}^{k} I_{jk}^{k}}{K} \quad (1)$$

K is the number of category indicators.

Jk = the number of k subcategories.

Weight is W. (score of the first standardized axis of category Jk)

I is a binary variable of the form 0/1 that corresponds to the Jk category.

Equation (1) for better interpretation is normalized as equation (2):

$$\tilde{C}_i = ((C_i - \min(\mathrm{C}))/(\max(C) - \min(C))) * 100 \quad (2)$$

Infodemic Exposure Index

The infodemic exposure index was constructed using two indicators. Conflict information on health topics encountered, representing the existence of wrong and accurate information and the feeling of overwhelmed they had with the volume of health information they received. Since the variables were categorical, we used multiple correspondent analysis. The final composite index ranged from 0(no exposure) to 1(high exposure).

Each index was validated through internal consistency testing and visualization of screen plots. We also made sure all variables contributed meaningfully to the constructed indexes. Index complements were used for better interpretation.

Data Analysis

Data Preparation

Survey data was exported from KoboToolbox as MS Excel file to SPSS. In SPSS v26, identifiers and names were removed. Categories were recorded and new variables created. The dataset was saved in .sav and CSV formats. The cleaned dataset was imported into Stata 17.

Description of the Statistical Methods Used

Data was summarized by three key domains: sociodemographic characteristics, exposure to health information, internet access and usage. Means, standard deviations, proportions were calculated. For inferential statistics, we applied Principal Component Analysis (PCA) for continuous variables, to extract uncorrelated components that capture most of the variance in digital literacy and official/unofficial information sources. For categorical and binary variables such as misinformation behavior and exposure to conflicting information, we used Multiple correspondence analysis. All the variables were normalized to (0 to 1) range for comparison. Ordinary Least squares (OLS) regression models were used to identify determinants of digital literacy and misinformation. The various developed indexes were the dependent variables. Sociodemographic factors (age, sex, education, income, residence, employment), cognitive variables (HBM, ELM scores), and information source variables (official and unofficial) were the independent variables. Statistical significance was assessed using 95% confidence intervals. Model validation included adjusted R-square, residual analysis, and multicollinearity testing (variance inflation Factor <3).

Results

Sociodemographic Characteristics of Participants

Participants were distributed per region, Center (17.7%), Littoral (16.1%), North (17.4%), South-west (14.2%), North-West (18.9%), and West (15.7%). Urban dwellers were 73.5%, while rural dwellers were 26.5%. females were 52.9% compared to males 47.1%. Young adults (18-34 years) were the largest group (52.6%), followed by middle-aged adults (35-54 years) 40.7%, and older adults (55+ years) 6.7%. In respect to education, 13.0% of the participants had no formal or only primary education, 46%1% completed secondary education, 30.0% were undergraduates, and 12.9% were postgraduates. In employment, 34.9% worked in the formal sector, 32.2% in the informal sector, and 32.9% were unemployed. For income levels, 52.3% reported low income, 17.0% middle income, and 4.2% high income, while 26.4% did not disclose their income (table 1).

Table 1. Sociodemographic Characteristics of Respondents (N = 1,439)

Variable	Category	Frequency	Percentage
Region	Centre	255	17.7
	Littoral	231	16.1
	North	250	17.4
	South-West	205	14.2
	North-West	272	18.9
	West	226	15.7
Residence	Rural	381	26.5
	Urban	1,058	73.5

Sex	Male	678	47.1
	Female	761	52.9
Age Group	18–34 years	757	52.6
	35–54 years	585	40.7
	55+ years	97	6.7
Education	No/Primary	187	13.0
	Secondary	664	46.1
	Undergraduate	402	30.0
	Postgraduate	186	12.9
Employment	Formal	502	34.9
	Informal	464	32.2
	Unemployed	473	32.9
Income	Low	753	52.3
	Middle	245	17.0
	High	61	4.2
	No response	380	26.4

Exposure to Health Information and Perceived Misinformation

Participants reported exposure to health information across several topics, six months prior to answering the questionnaire (table 2). The most encountered topics were non communicable diseases (52%), HIV/AIDS (49.8%), and malaria (46.8%). Vaccine related information was also common: 33.6% on routine immunization and 20.4% on other vaccines. Fewer participants encountered maternal and child health information (27%) and COVID-19 (23.4%).

Perceived misinformation was high across health topics. More than half of the participants suspected that the information they encountered on HIV/AIDS (54%) and non-communicable diseases (52%) was misleading. Vaccine related content showed similar trend, with 46.8% expressing doubts about routine immunization and 49.8% about other vaccines.

Table 2. Health Topics Encountered and Perceived Misinformation (N = 1,439)

Disease/health program	% Encountered Information	% Suspected Misinformation
COVID-19	23.4	23.4
Routine Immunization	33.6	46.8
Other Vaccines	20.4	49.8
Malaria	46.8	20.4
HIV/AIDS	49.8	54.0
Maternal & Child Health	27.0	27.0
Non-Communicable Diseases	52.0	52.0

Participants reported encountering conflicting health information across topics (Table 3). Almost half reported this rarely (45%), about one third reported it sometimes (28.2%), small groups faced it often (13.3%), always (5.1%) and 7.3% reported never encountering conflicting health information. Mean frequency score (table 4) was 1.64 on a scale of 0 to 4 (SD 0.98), where 0 means never and 4 means always.

Table 3. Frequency of Encountering Conflicting Information (N = 1,439)

Frequency	Counts	Percentage
Never	105	7.3%
Rarely	656	45.6%
Sometimes	406	28.2%
Often	199	13.8%
Always	73	5.1%

Table 4. Mean Frequency Score for Encountering Conflicting Information (N = 1,439)

Variable	Mean	Std. Dev	minimum	maximum
Frequency of Conflicting Info	1.64	0.98	0	4

The sources of this conflicting information were informal and formal. Social media was the highest with 74.5%, followed by family and friends 63.4%. formal channels had lower frequencies: Health facilities (19.1%), News outlets (17%), government websites (12.9%), Health forums (11.3%), Health NGOs (9.2%), mobile health apps (9.0%), and academic journals (4.0%) (Table 5).

Table 5. Sources of Conflicting Health Information(N=1,439)

Source	Frequency	Percentage
Social media	1071	74.5%
Family/Friends	911	63.4%
Health Facilities	275	19.1%
News Outlets	245	17.0%
Government Websites	186	12.9%
Health Forums	163	11.3%
Health NGOs	133	9.2%
Mobile Health Apps	130	9.0%
Academic Journals/Pubs	58	4.0%

The participants emotional responses to the volume of health information all sources combined showed (table 6): slightly overwhelmed was most common (37.7%), followed by moderately overwhelmed (28.6%). A smaller group felt very overwhelmed (13.4%) or extremely overwhelmed (3.1%). About one six reported not feeling overwhelmed (17.2%). The mean overwhelm score (table 7) was 1.47 on a scale of 0 to 1(SD 1.02), where 0 means not at all and 4 means extremely.

Table 6. Frequency of Overwhelm Levels (N = 1,439)

Level of Overwhelm	Frequency	Percentage
Not at all overwhelmed	248	17.2%
Slightly overwhelmed	543	37.7%
Moderately overwhelmed	411	28.6%
Very overwhelmed	193	13.4%
Extremely overwhelmed	44	3.1%

Table 7. Mean Overwhelm Levels (N = 1,439)

Variable	Mean	Std. Dev	minimum	Maximum
Feeling Overwhelmed	1.47	1.02	0	4

Combining the frequency of encountering conflicting health information and the level of overwhelm to the volume of health information gave us an Infodemic exposure index with a mean score of 0.389(SD=0.219), indicating moderate exposure across the participants. Misinformation behavior index score was 0.706 (SD=0.2369), meaning 70% of the participants reported they had adopted harmful health behavior as result of misinformation (table 8).

Table 8. Summary Statistics of the Infodemic Exposure Index and Misinformation Behavior Index (N = 1,439)

Index	Mean	Standard Deviation	Minimum	Maximum
Infodemics (MCA-based)	0.389	0.219	0	1
Complement Infodemics	0.611	0.219	0	1
Misinformation index (constructed using MCA)	0.7059	0.2369	0	1
complement Misinformation index	0.2941	0.2369	0	1

Internet Access and Digital Literacy

Most of the participants access internet primarily via smartphones (83.9%), followed by computers or laptops (22.0%) and basic phones with little connectivity (16.8%). Only 4.2% used tablets, and 1.2% relied on cyber cafés, while 0.3% of the participants reported no internet use (table 9).

Table 9. Devices used to Access the Internet (N = 1,439)

Device	Users (n)	Users (%)
Smartphone	1,160	83.9
Basic phone	232	16.8
Computer/Laptop	304	22.0
Cyber café	16	1.2
Tablet	58	4.2
No internet use	4	0.3

In respect to how often they connect to the internet, 45.6% reported being “always” online, 22.1% “sometimes”, 19.0% “often”, 9.4% “rarely” and 4.0% “never” (table 10).

Table 10. Internet Usage Frequency (N = 1,439)

Frequency	Respondents	Percentage
Never	57	4.0
Rarely	135	9.4
Sometimes	318	22.1
Often	273	19.0
Always	656	45.6

The mean internet engagement score was 2.93 (SD= 1.185), with a minimum of 0 and maximum of 4, showing a moderate to high digital engagement amongst participants (table 11).

Table 11. Mean Internet Engagement

	N	Minimum	Maximum	Mean	Std. Deviation
Internet Usage Freq	1439	0	4	2.93	1.185
Valid N (listwise)	1439				

Using the PCA, we constructed a digital literacy index. The mean was 0.397(SD=0.197), indicating that approximately 39.7% of participants were digitally literate (index ≥ 0.5). The remaining 61.1% had low digital literacy levels (table 12).

Table 12. Descriptive Statistics for the Digital Literacy Index (N = 1,439)

Index	Mean	Standard Deviation	Minimum	Maximum
Digital Literacy Index (PCA-based)	0.397	0.197	0	1
Complement Digital Literacy Index	0.603	0.197	0	1

Determinants of Digital Literacy and Misinformation

Digital Literacy Model

The following factors were positively associated with digital literacy (table 13): Trusting official sources for information (β= 0.234, SE 0.0263, p< 0.01), unofficial sources (β= 0.146, SE 0.0302, p < 0.01). Higher Health Believe Model scores (β= 0.027, SE 0.0066, p< 0.01), male score higher than female (β= 0.025, SE 0.0104, p< 0.05), High income (β= 0.048, SE 0.0276, p< 0.10). Post graduate education had a greater association (β= 0.279, SE 0.0328, p < 0.01) followed by undergraduate (β= 0.232, SE 0.0306, p < 0.01) and secondary (β= 0.147, SE 0.0291, p < 0.01). Concerning age, the young adults scored higher (β = 0.093, SE 0.0212, p < 0.01). Many factors were negatively associated with digital literacy. Susceptibility to misinformation (β= -0.052, SE 0.0217, p < 0.05), reliance on peripheral route (β= -0.082, SE 0.0201, p < 0.01), informal employment (β= -0.066, SE 0.0134, p < 0.01), unemployment (β= -0.074, SE 0.0134, $p < 0.01$), and residing in rural areas (β= -0.061, SE 0.0125, $p < 0.01$). Model fit was moderate to strong (adjusted $R^2 = 0.3459$).

Misinformation Model

Trust in official source was positively associated with Misinformation (β= 0.096, SE 0.0329, $p < 0.01$). The HBM scores showed a small positive association (β= 0.015, SE 0.0080, $p < 0.10$). High income was also positively associated (β= 0.100, SE 0.0335, $p < 0.01$). younger age groups were more susceptible to misinformation. young adults (β= 0.068, SE 0.0264, $p < 0.01$) and middle-aged adults (β= 0.053, SE 0.059, $p < 0.05$). Factors like the digital literacy index (β= -0.078, SE 0.0322, $p < 0.05$) and trust in unofficial sources for information (β= -0.129, SE 0.0369, $p < 0.01$) were negatively associated with misinformation susceptibility. Model fit was modest (adjusted $R^2 = 0.0676$) (table 13).

Table 13. Determinants of Digital Literacy and Misinformation (N = 1,439)

Variables		
Dependent Variable	**Digital literacy index**	**Misinformation behavior index**
Digital literacy index	--------	-0.078** (0.0322)
Misinformation index	-0.052** (0.0217)	-------
Official sources	0 .234*** (0.0263)	0.096*** (0.0329)
Unofficial sources	0.146*** (0.0302)	-0.129*** (0.0369)
HBM	0.027*** (0.0066)	0.015* (0.0080)
Peripheral route	-0.082*** (0.0201)	0.171 (0.0242)
Sex (Male=1 0 otherwise)	0.025** (0.0104)	0.002 (0.0126)
Level of Income (high=1; 0 otherwise	0.048* (0.0276)	0 .100*** (0 .0335)
Level of Income (middle =1; 0 otherwise	-0.020 (0.0147)	0.029 (0 .0179)
Level of education (Postgraduate=1; 0 otherwise)	0.279*** (0.0328)	0.039 (0 .0409)
Level of education (undergraduate=1; 0 otherwise)	0.232*** (0.0306)	0.030 (0.0380)
Level of education (secondary=1; 0 otherwise)	0.147*** (0.0291)	0 .039 (0 .0359)
Level of education (Primary=1; 0 otherwise)	0.052 (0.0320)	0 .028 (0 .0390)

Sector of employment (informal sector =1; 0 otherwise)	-0.066*** (0.0134)	-0 .005 (0 .0165)
Employment status (Unemployed=1; 0 otherwise)	-0.074*** (0.0134)	0.011 (0.0164)
Area of resident (Rural=1; 0 otherwise)	-0.061*** (0.0125)	-0.016 (0.0154)
Age Group (young adult=1; 0 otherwise)	0.189*** (0.0215)	0.068*** (0.0264)
Age Group (middle-aged adult=1; 0 otherwise)	0.093*** (0.0212)	0.053** (0.059)
Constant	-0.008 (0.0411)	0.506*** (0.0520)
Adjusted R-Squared	0.3459	0.0676
Number of observations	1,439	1,439

Source: *Constructed by author using STATA 17.0. Values in paratheses indicate standard errors. ***, **and * indicates significant level by 1%, 5% and 10% respectively.*

Discussion

This study embarked on examining the breath of infodemics and misinformation exposure across multiple health topics in Cameroon. It also examined the level of digital literacy of participants. Key determinants of misinformation susceptibility and digital literacy were identified. These determinants are sociodemographic characteristics, cognitive and information sources. The findings shed light on important issues that have significant implications in public health communication, digital literacy interventions and the management of infodemics and misinformation in Cameroon and low-and-middle-income countries (LMIC).

Findings showed that misinformation and conflicting health information do not only occur in epidemic or public health emergency situations (such as COVID-19) but extend a wide range of diseases and health programs in Cameroon. Routine immunization, other vaccines, HIV/AIDS, malaria, non-communicable diseases and maternal and child health experience some degree of conflicting information and misinformation. This aligns with emerging evidence that infodemics are not episodic but a routine phenomenon. An editorial from the Panamerican Journal of Public Health talks of infodemic like a rapid, large-scale dissemination of all kinds of health information and misinformation, some accurate and some not, that makes it harder for people to find trustworthy sources and reliable guidance when needed [15]. In this light the CDC acknowledged the fact that infodemics surveillance activities are also important in routine non-emergency setting and may cover nutrition and cancers programs[16]. The exposure in our sample was moderate (mean infodemic exposure index=0.389, Sd= 0.219) but sufficiently widespread to warrant concern. When we unpack the infodemic construct into the exposure of conflicting information and the feeling overwhelmed to the volume of information, nearly half of respondents reported encountering conflicting health information rarely (45%), 28.2% sometimes, 13.8% often, and 5.1% always. The fact that

37.7% reported feeling slightly overwhelmed, and 13.4% very overwhelmed points to the emotional aspect of infodemics. This could trigger anxiety, confusion and disengagement[17].

Conflicting health information was more prominent in social media (74.5%), followed by family and friends (63.4%), while formal channels such as health facilities (19.1%) and news outlets (17.0%) were less frequently reported as source of conflicting information by participants. This corroborates other studies which cite social media and interpersonal networks as the main source of health information [18]. Furthermore, people encounter conflicting information when searching or passively, when they receive it on their phones or from family and friends. This conflicting information may originate from formal channels or from informal networks like social media platforms which are increasingly important[19]. The implication is that intervention focused solely on formal channels may miss the interpersonal networks. The ability of people to identify reliable information and act on it is key to improving public health. Thus, digital literacy is a primary intervention.

The results on digital access and literacy are revealing. Although 83.9% of participants could access the internet primarily via smartphones, the mean Digital Literacy Index was 0.397 (SD=0.197) meaning only 39.7% of the participants were classified as "digitally literate" (index ≥ 0.5). This digital literacy rate is lower to that obtained (43.6%) in Southwest Ethiopia among healthcare providers[20]. This difference could be due to sample composition and measuring scale. The disparity between digital access and critical digital skills reflects what has been termed the "digital divide 2.0"[21]. Where people have access to the internet but do not automatically translate into equal capability to evaluate, interpret and apply digital information. The fact that rural residence, informal employment, unemployment, and lower education were strongly associated with lower digital literacy confirms that structural inequalities shape digital literacy outcomes[22, 23]. The implication is that digital literacy interventions should be able to address these inequalities for it to be efficient.

The multivariate regression models clarified the determinants of digital literacy and misinformation susceptibility. Higher level of education: Postgraduate, undergraduate and secondary school were strongly associated with higher digital literacy scores. Higher income also showed a positive association, though marginal. On the other hand, living in a rural residence, unemployment, and using the peripheral processing pathway were negatively associated with digital literacy. These findings are consistent with literature that align structural and cognitive factors to digital literacy disparities [22–24]. A reciprocal association was observed between misinformation susceptibility and digital literacy (β= -0.052; $p< 0.05$, β = -0.078; $p<0.05$ respectively). This suggests that digital literacy and misinformation susceptibility are mutually reinforcing processes. Improving digital skills may reduce vulnerability to misinformation, and vice versa. This finding is consistent with a study conducted in the united state of America, which also showed there is a reciprocal association between these two constructs[25].

The misinformation regression model identified several socio-demographic and informational predictors of susceptibility to health misinformation. Trust in official sources showed a positive and significant association with misinformation susceptibility (β= 0.096; $p<0.01$). This is unexpected, because studies have shown a protective effect of official sources on misinformation. This indicates that higher engagement with official sources does not necessarily protects from misinformation. A possible explanation is that people who are highly engaged with official sources may also be more exposed to large volume of health information, including conflicting messages.

Unofficial sources were negatively associated with misinformation (β= - 0.129; $p<0.01$). which means that in this dataset, people who reported using more unofficial sources had lower levels of susceptibility to misinformation. This could be explained by more active cross-verification or unofficial sources like community leaders or trusted peers who correct misinformation. Younger age groups (young adults β= 0.068; middle age β= 0.053) were more susceptible to misinformation compared to older adults. Higher income (β= 0.100; $p<0.01$) was positively associated with misinformation susceptibility. This aligns with other studies suggesting that younger individuals, though digitally active, may lack critical digital literacy skills needed to filter false information. Their higher exposure through online platforms could also contribute to increased vulnerability. High income earners are potentially exposed to greater internet access or engagement without necessarily strong critical evaluation skills[26]. Despite these associations, the model fit was modest (adjusted R^2 =0.0676) suggesting other factors outside the model may also influence susceptibility to misinformation but were not captured in this model.

In General, the findings show a layered model of infodemic vulnerability: structural (education, income, place of residence), informational (source of information, and exposure frequency), cognitive (digital literacy, processing route) and behavioral (misinformation related actions) all interacting. Previous research in African context has pointed to digital literacy as a key protective factor [27].

Strengths and Limitations

The study has a large sample size (N=1,439), conducted across six regions covering rural/urban, conflict-zones, and Cameroon's cultural and linguistic diversity. The use of composite indices Strengthens internal consistency and construct validity valid. However, it is a cross-sectional study design, with self-reported measures of exposure and behavior that may be subject to recall or social desirability bias. To reduce recall bias, participants were asked to report experience within the past six months. The study is non probabilistic sampling, meaning the findings are not strictly generalizable to the entire country. Further research should include longitudinal and experimental designs evaluating literacy and fact-checking interventions.

Recommendations and Practical Implications

Following our findings, these five key recommendations to reduce misinformation and strengthen digital literacy emerge:

1. Build digital health literacy in vulnerable groups: Target rural, low income, informal sector workers and women. Teach people how to evaluate, cross-check, and apply digital health information.
2. Integrate digital and health literacy into education and outreach: Embed into school curricula, adult learning, and community outreach.
3. Use misinformation channels as delivery platforms: partner with local influencers, religious leaders, and WhatsApp group administrators. Share trusted, actionable content and encourage peer verification in social and interpersonal networks.
4. Monitor infodemics and respond quickly: Use social listening (e.g., WhatsApp, Facebook) to detect harmful health narratives early.
5. Promote analytical thinking through debunking and fact-checking: design strategies that support critical evaluation (central route processing) to build long-term resistance.

Conclusion

This study addresses a present public health challenge in Cameroon: The significant exposure to health related infodemics and misinformation across multiple diseases and health programs. The findings showed a moderate yet prevalent exposure to conflicting health information, a predominant dependence on social media and interpersonal networks, and significant gaps in digital literacy. It was demonstrated that higher literacy is associated with lower susceptibility to misinformation even though vulnerable groups (lower education, rural residence, informal employment) are more likely to be susceptible to misinformation. The results have both theoretical and practical significance: they empirically validate composite indices of infodemic exposure, digital literacy and misinformation behavior; they extend the conceptual model of infodemic vulnerability beyond epidemic crises into routine health promotion; and they provide actionable evidence for designing targeted interventions in LMIC. To improve resilience against misinformation and support informed health decisions, stakeholders must invest in digital literacy programs, reinforce trust in formal communications sources and integrate infodemic management and surveillance into routine health systems. The challenge is real and urgent, but with a strategic, equity-oriented approach, the risk posed by infodemics can be mitigated.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Gerard Epie Kepche: Conceptualization, Methodology, Formal analysis, Writing, original draft.
Tendongfor Nicholas: Data curation, Validation, Writing, review and editing.
Anweh Vera Njang: Data analysis and editing.

Acknowledgements

The authors thank regional communication focal persons for the 6 regions, district health teams, survey enumerators, and all study participants.

Funding

This study was self-funded, the researchers received no external funding.

References

[1]. Kbaier, D., Kane, A., McJury, M., and Kenny, I., 2024, Prevalence of health misinformation on social media—challenges and mitigation before, during, and beyond the covid-19 pandemic: Scoping literature review. *Journal of Medical Internet Research,* 26, https://doi.org/10.2196/38786.

[2]. Tomes, N., and Parry, M. S., 2022, What are the historical roots of the COVID-19 infodemic? Lessons from the past. Health Evidence Network Synthesis Report, No. 77, *Copenhagen: WHO Regional Office for Europe.*

[3]. Suarez-Lledo, V., and Alvarez-Galvez, J., 2021, Prevalence of health misinformation on social media: systematic review. *Journal of medical Internet research,* 23(1), https://doi.org/10.2196/17187.

[4]. Penka, M. B., Tangang, A., Alang Wung, E., Tata Kelese, M., and Okwen, P., 2024, Addressing infodemic for pandemic preparedness in the digital age: a focus on Middle Africa. *Front. Public Health,* 12:1275702, https://doi.org/10.3389/fpubh.2024.1275702.

[5]. Mabou Tagne, A., Biapa Nya, P. C., Tiotsia Tsapi, A., Edingue Essoh, A. K., Pembouong, G., Ngouadjeu Ngnintedem, M. A., et al., 2019, Determinants, prevalence and trend of use of medicinal plants among people living with HIV: a cross-sectional survey in Dschang, Cameroon. *AIDS and Behavior,* 23(8), https://doi.org/10.1007/s10461-018-02388-2.

[6]. Yahya, M., 2007, Polio vaccines—“no thank you!” barriers to polio eradication in Northern Nigeria. *African Affairs,* 106(423),185-204, https://doi.org/10.1093/afraf/adm016.

[7]. Fung, I. C. H., Fu, K. W., Chan, C. H., Chan, B. S. B., Cheung, C. N., Abraham, T., and Tse, Z. T. H., 2016, Social media's initial reaction to information and misinformation on Ebola, August 2014: facts and rumors. *Public health reports,* 131(3),461-73, https://doi.org/10.1177/003335491613100312.

[8]. Linonge-Fontebo, H. N., and Baloye, M. E., 2024, Responses of Christians to COVID-19 policies: A case study of selected BONAVADA Pentecostal churches, Cameroon. *African Journal of Pentecostal Studies*, 1(1), https://doi.org/10.4102/ajops.v1i1.28

[9]. Myemba, D. T., Smets, L., Sunguya, B. F., Vandaele, N., and Decouttere, C., 2025, Challenges and strategies for sustainable and resilient immunization systems in sub-Saharan Africa: A comprehensive scoping review. *Vaccine*, 45, https://doi.org/10.1016/j.vaccine.2024.126639

[10]. Bowen, H. L., 2013, Impact of a mass media campaign on bed net use in Cameroon. *Malaria journal*, 12(36).

[11]. Olaoye, A., and Onyenankeya, K., 2023, A systematic review of health communication strategies in Sub-Saharan Africa-2015-2022. *Health Promotion Perspectives*, *13*(1), 10-20, https://doi.org/10.34172/hpp.2023.02.

[12]. Kisa, S., and Kisa, A., 2024, A comprehensive analysis of COVID-19 misinformation, public health impacts, and communication strategies: scoping review. *Journal of Medical Internet Research*, *26,* https://doi.org/10.2196/56931.

[13]. Eysenbach, G., 2020, How to fight an infodemic: the four pillars of infodemic management. *Journal of medical Internet research*, *22*(6), https://doi.org/10.2196/21820.

[14]. Tatchim, N., 2024, The ‘‘Anglophone crisis’’ in Cameroon: cultural diversity as governmentality of (post) colonial divide. *Journal of Ethnic and Diversity Studies (JOEDS)*, *2*(2).

[15]. García-Saisó, S., Marti, M., Brooks, I., Curioso, W. H., González, D., Malek, V., et al., 2021, The COVID-19 infodemic. *Revista panamericana de salud pública*, *45*, https://doi.org/10.26633/RPSP.2021.56.

[16]. Chiou, H., Voegeli, C., Wilhelm, E., Kolis, J., Brookmeyer, K., and Prybylski, D., 2022, The future of infodemic surveillance as public health surveillance. *Emerging Infectious Diseases*, *28*(Suppl 1), https://doi.org/10.3201/eid2813.220696.

[17]. Sathianathan, S., Mhd Ali, A., and Chong, W. W., 2025, How the General Public Navigates Health Misinformation on Social Media: Qualitative Study of Identification and Response Approaches. *JMIR infodemiology*, *5*, https://doi.org/10.2196/67464.

[18]. Cohen, K. S., Fallik, D., and Cappola, A. R., 2025, The Role of Family as a Source of Health Information Among College Students. *Journal of Community Health*, 50, 613-622, https://doi.org/10.1007/s10900-025-01448-8

[19]. Carpenter, D. M., Geryk, L. L., Chen, A. T., Nagler, R. H., Dieckmann, N. F., and Han, P. K., 2016, Conflicting health information: a critical research need. *Health Expectations*, 19(6), 1173-1182, https://doi.org/10.1111/hex.12438.

[20]. Ahmed, M. H., Guadie, H. A., Ngusie, H. S., Teferi, G. H., Gullslett, M. K., Hailegebreal, S., et al., 2022, Digital health literacy during the COVID-19 pandemic among health care providers in resource-limited settings: cross-sectional study. *JMIR Nursing*, *5*(1), https://doi.org/10.2196/39866.

[21]. Van Dijk, J. A. G. M., 2017, Digital divide: Impact of access, edited by P. Rössler., C. A. Hoffner., and L. V. Zoonen., *The international encyclopedia of media effects, JohnWiley and Sons, Inc*, https://doi.org/10.1002/9781118783764.wbieme0043.

[22]. ALIYU, Z., and ABDULLAHI, F. A., 2025, A COMPARATIVE ANALYSIS OF DIGITAL LITERACY AMONG RURAL AND URBAN STUDENTS. *International Journal of Modeling and Applied Science Research*, 7, https://doi.org/10.70382/caijmasr.v7i9.004.

[23]. Fang, W., and Nie, C., 2025, Inequalities in digital literacy: exploring the disparity in tangible outcomes of internet use among college students in China. *Frontiers in Communication*, *10*, https://doi.org/10.3389/fcomm.2025.1601240.

[24]. Raihan, M. M., Subroto, S., Chowdhury, N., Koch, K., Ruttan, E., and Turin, T. C., 2025, Dimensions and barriers for digital (in) equity and digital divide: A systematic integrative review. *Digital Transformation and Society*, *4*(2), 111-127, https://doi.org/10.1108/DTS-04-2024-0054.

[25]. Gaysynsky, A., Senft Everson, N., Heley, K., and Chou, W. Y. S., 2024, Perceptions of health misinformation on social media: cross-sectional survey study. *Jmir Infodemiology*, *4*, https://doi.org/10.2196/51127.

[26]. Kops, M., Schittenhelm, C., and Wachs, S., 2025, Young people and false information: A scoping review of responses, influential factors, consequences, and prevention programs. *Computers in Human Behavior*, 169, https://doi.org/10.1016/j.chb.2025.108650.

[27]. Choukou, M. A., Sanchez-Ramirez, D. C., Pol, M., Uddin, M., Monnin, C., and Syed-Abdul, S., 2022, COVID-19 infodemic and digital health literacy in vulnerable populations: a scoping review. *Digital health*, *8*, 1-13, https://doi.org/10.1177/20552076221076927.