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A mixed cross-sectional study with natural language processing analysis on computer literacy and access among healthcare workers in Guinea

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Abstract

Background: According to the World Health Organization (WHO), technology is the backbone of services to prevent, diagnose, and treat diseases. In this context, it is important to evaluate health workers' mastery of basic computer skills. This study aimed to assess the level of mastery of basic computer skills among health workers in Guinea and identify the factors that influence this computer skill mastery to propose ways to improve it.

Methods: A mixed cross-sectional study was conducted, with data analysed in two phases: descriptive analysis and logistical regression analysis for quantitative data, sentiment analysis, word cloud analysis, and qualitative content analysis for qualitative data. Python3.8 was used for all data analyses.

Results: Data were collected from 408 health workers serving in different health districts in Guinea. The proportion of healthcare workers with basic computer skills was 22.5% (92 participants). The sentiment analysis showed a highly negative sentiment (VADER compound score=-0.992) in the text analysed, which may be due to the various challenges and barriers highlighted by the respondents, such as the lack of software and training centres, limited access to computers, unstable electricity and internet connectivity, lack of computer skills and training, and barriers to access computers. The word cloud analysis indicated that the most frequent topics discussed in the text were related to "software," "lack," "electricity," "connection," "mastery," "obstacles," and "training."

Conclusion: This study highlights the challenges and barriers health workers face in accessing and using computer tools in Guinea. It is necessary to address these challenges by providing access to computer tools, improving electricity and internet connectivity, and enhancing computer skills and training for health workers.

Keywords: computer skills, health workers, sentiment analysis, Guinea

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1. Introduction

According to the World Health Organization (WHO), technologies form the backbone of services to prevent, diagnose and treat disease[1]. Since May 2005, the 58th World Health Assembly has adopted a resolution on electronic health (e-health), calling on WHO member countries to use e-health to pursue the vision of health for all[2]. To achieve this, the use of computers would be essential. There are many examples of portable computers in healthcare, including electronic prescription, diagnosis and patient advice, examination of patients, practice management, reminder notifications and e-learning[3.4]. Healthcare personnel now have instant access to vast amounts of information, including X-ray results, lab tests, primary and pre-reviewed research databases, clinical practice guidelines and reference guides on medication[5].

International studies have shown a reduction in medication prescriptions, a decrease in adverse drug events, a reduction in the double-ordering of tests, and a decline in costs[6.7].

Many sub-Saharan African countries have already implemented telemedicine projects. However, most of them need help with adequate ICT infrastructure, which creates suboptimal utilization of this technology. Moreover, another issue is that healthcare workers need to be more proficient in using computer tools [8].

The health sector in Guinea faces several challenges, including a shortage of qualified personnel and limited access to information and communication technologies. Therefore, it is crucial to assess the proficiency of healthcare workers in using computer tools. Our study aimed to evaluate the level of mastery of basic computer tools among healthcare workers in Guinea and identify the factors that influence this proficiency to propose solutions to improve their computer skills.

2. Subjects and Methods

2.1 Type and framework of the study

This study was conducted in Conakry, the capital city of the Republic of Guinea. It targeted health facilities to assess the computer skills of health workers, regardless of their profession or level of experience. To ensure the accuracy and reliability of the results, both qualitative and quantitative questionnaires were administered by trained collectors. The study design aimed to comprehensively evaluate health workers' challenges and barriers in effectively using computer tools.

2.2 Sampling and sample size

The Swartz sampling method was used to select a representative sample of health workers for a computer literacy study. Since the proportion of health workers with computer literacy skills was unknown, a maximum possible variability of 50% was assumed. The sample size was determined using the formula n = Z^2 * p * (1-p) / e^2, with a 95% confidence level and a margin of error of 5%. A sample size of 384.16 was obtained, rounded up to 385. Participants were selected using a random sampling technique, with a list of all health workers in the target population and a random number generator. An assumption of 50% for the proportion of health workers with computer literacy skills was made. However, the sample proportion (p-hat) was later calculated from the sample data to adjust the sample size using the formula n' = n * (p-hat * (1 - p-hat)) / (p * (1 - p)). Assuming a sample proportion of 0.6, the adjusted sample size was calculated as 408 participants. Therefore, the sample size was adjusted from 385 to 408 to account for the proportion of health workers with computer literacy skills.

2.3 Data Collection

Structured survey questionnaires and interviews were used to collect data. The survey questionnaires were administered through face-to-face interviews. The survey consisted of questions regarding computer knowledge, frequency of computer use, and factors that may influence computer use. The interviews focused on the participants' experience using computers and the obstacles they may face.

2.4 Description of variables

The variables studied in this survey relate to the characteristics of health workers in Guinea, such as their place of residence, sex, their age, and diploma level. The health structure and service in which they work and their number of years of experience are also considered. In addition, variables related to the practical use of computer tools were collected, such as the types of computers used, the number of years and hours of use per week, the need for assistance in using computers, interest in using computers for health-related activities, and level of confidence in using computers in general and for health-related activities. The variables related to the practical application of computer tools were consolidated into scores, with agents scoring above 50% considered proficient in using computers for basic work tasks in their work context. This variable was then compared against patient characteristics to identify factors associated with this level of proficiency. These variables are important to better understand computer skills and the use of related tools among health workers in Guinea.

2.5 Data Analysis

Data analysis was conducted in two phases: descriptive analysis and logistical regression analysis for the quantitative data, sentiment analysis, word cloud analysis, and qualitative content analysis for the qualitative data. All analyses were conducted using Python3.8. Descriptive statistics such as mean, median, and standard deviation were used to summarise the data. Logistic regression was used to estimate factors associated with computer use among healthcare professionals. Examining factors were selected based on a literature review and expert opinions. A p-value of less than 0.05 was considered statistically significant.

Responding to open-ended questions were examined to analyse participants' opinions on computer use. Natural language processing tools such as the Natural Language Toolkit (NLTK) library and the VADER tool were used to conduct sentiment analysis. A word cloud was created from participants' responses to identify the most commonly used words related to computer use. The study was conducted using Python software and presented visually using the WordCloud library. Finally, we conducted content analysis to identify themes and patterns related to computer use identified by the word cloud. The analysis used a coding framework based on a literature review and expert opinions. The results were presented in text form.

3. Results

3.1.Results of the quantitative part

In this study, we collected data from 408 healthcare workers in various healthcare facilities in Guinea. The proportion of healthcare workers with basic computer skills was 22.5% (92 participants). Men were more involved in basic computer skills, with 80% (Table 1) of them being male, with a significant difference (p-value <0.001). Users with computer basic skills had a relatively high median age of 38 (30, 45) years with a significant difference (p-value = 0.010). General practitioners and nurses were the most dominant in the group of users who had basic computer skills, accounting for 42% and 33%, respectively (p-value <0.001).

Table (1) Characteristics of health workers according to proficiency in computer use

Features	Proficiency in computer use		p-value
	No, N=316	Yes, N=92	
Place of residence, n (%)			0.4
Urban	233 (74%)	72 (78%)	
Rural	83 (26%)	20 (22%)	
Sex, n (%)			<0.001
Male	153 (48%)	74 (80%)	
Feminine	163 (52%)	18 (20%)	
Age in years, Median (IQR)	34 (28, 39)	38 (30, 45)	0.010
Highest degree, n (%)			<0.001
General practitioner	48 (15%)	39 (42%)	
Specialist	6 (1.9%)	6 (6.5%)	
Laboratory Assistant	44 (14%)	10 (11%)	
health aid	62 (20%)	7 (7.6%)	
State nurse	156 (49%)	30 (33%)	
Type of health facility, n (%)			
University Hospital/National Hospital	15 (4.7%)	11 (12%)	
Regional hospital	68 (22%)	8 (8.7%)	
Prefectural Hospital/CMC	64 (20%)	36 (39%)	
Health centre	134 (42%)	31 (34%)	
Health post	25 (7.9%)	0 (0%)	
Another type	10 (3.2%)	6 (6.5%)	
Service, n (%)			0.8

General medicine	83 (26%)	25 (27%)	
Paediatrics	38 (12%)	15 (16%)	
Laboratory	41 (13%)	13 (14%)	
SMIT	34 (11%)	8 (8.7%)	
Other (explain, list)	120 (38%)	31 (34%)	
Number of years of experience, Median (IQR)	6 (3, 10)	8 (4, 13)	0.005

The mastery of basic computer skills (Table2) varied according to gender [ORa = 0.30 (95% CI: 0.16-0.54), p-value <0.001], [ORa = 0.30 (95% CI: 0.16-0.54), p-value <0.001], education level, including laboratory technicians [ORa = 0.28 (95% CI: 0.12-0.62), p-value = 0.002], healthcare aides [ORa = 0.18 (95% CI: 0.07-0.42), p-value <0.001], and state nurses [ORa = 0.33 (95% CI: 0.18-0.60), p-value <0.001].

Table (2) Logistic regression of the characteristics of health workers on the mastery of the use of the computer tool

Features	OR adjusted	95% CI	p-value
Sex			
Male	—	—	
Feminine	0.30	0.16, 0.54	<0.001
Age in years	1.00	0.97, 1.04	0.8
Highest degree			
General practitioner	—	—	
Specialist	1.01	0.28, 3.68	>0.9
Laboratory Assistant	0.28	0.12, 0.62	0.002
health aid	0.18	0.07, 0.42	<0.001
State nurse	0.33	0.18, 0.60	<0.001
Number of years of experience	1.02	0.97, 1.07	0.4

Laptops were the most common among the types of computers used (82%), followed by desktop computers (31%). In our study, 66% of healthcare workers using a computer expressed a need for assistance, including software installation, configuration, and usage (data entry and analysis), with respective proportions of 48%, 56%, and 65%. We observed that 89% of users would like to use the computer for health-related activities. The evaluation of the confidence level in using a computer showed 16% for "Not at all confident" and 34% for "Very confident". The confidence level remained close for health-related activities, with 17% for "Not at all confident" and 34% for "Very confident" (Table 3).

Table (3) Characteristics of computer-using health workers according to practice

Characteristic	Effective (%) N=176
Types of computers used, n (%)	
Office automation	55 (31%)
Portable	145 (82%)
Tablet (e.g. iPad)	21 (12%)
smartphone	17 (9.7%)
Other	1 (0.6%)
Number of years of computer use, median (IQR)	12 (5, 48)
Number of hours of computer use per week, median (IQR)	8 (2, 21)

Need help using the computer, n (%)	
No	59 (34%)
Yes	117 (66%)
Type of need, n (%)	
Facility	56 (48%)
Software settings	66 (56%)
Use of software (entry, analysis, etc.)	76 (65%)
Turn off the computer	3 (2.6%)
Do you like to use the computer for health-related activities?, n (%)	
No	19 (11%)
Yes	157 (89%)
Please rate your confidence in using a computer or related technology for general purposes, n (%)	
Not at all confident	28 (16%)
somewhat unsure	26 (15%)
Uncertain	20 (12%)
A little confident	44 (26%)
very confident	54 (31%)
Unknown	4
Please rate your confidence in using a computer or related technology for health-related activities, n (%)	
Not at all confident	30 (17%)
somewhat unsure	28 (16%)
Uncertain	13 (7.6%)
A little confident	43 (25%)
very confident	58 (34%)
Unknown	4

3.2.Results of the qualitative part

According to the participants' feedback, there are various barriers that health workers face when it comes to mastering computer tools. One major obstacle is the lack of access to necessary software and training centres. One health worker stated, "There are no training centres or facilities that offer computer training to health workers, making it difficult for us to improve our skills." Similarly, limited access to computers in health centres also poses a challenge, as noted by another respondent: "There are not enough computers in our health centre to allow all health workers access."

In addition to limited access to software and hardware, unstable electricity and the lack of Internet connectivity were also identified as significant barriers. Health workers reported that unstable electricity made it difficult to use computers consistently, while limited internet connectivity prevented access to online resources and collaboration with others. As one respondent stated, "We have limited access to the internet, which makes it difficult for us to access important information and resources online." Furthermore, health workers' lack of computer skills and knowledge was identified as a significant challenge. Many health workers reported lacking the necessary training and expertise to use computer tools effectively, such as word processing, spreadsheet, and database.

Barriers to computer access were also reported, including geographical isolation, lack of transportation, and limited financial resources. For example, one respondent highlighted the challenge of remote health centres, stating that "some health centres are located in remote areas, making it difficult for health workers to access computers and training centres." Finally, the lack of access to computer training programs focusing on specific skills, such as word processing, spreadsheet, and database software, was also identified as a barrier. One respondent commented, "There are no training programs available for health workers that focus on computer skills."

3.3.Sentiment Analysis

The sentiment analysis result using VADER on the survey about the mastery of basic computer skill by health workers shows a compound score of -0.992 (fig1). VADER's compound score ranges from -1 (extremely negative) to +1 (extremely positive), with 0 being neutral. Therefore, the compound score of -0.992 indicates a highly negative sentiment in the text analysed. This negative sentiment could be due to the various challenges and barriers highlighted by the respondents in the survey, such as the lack of software and training centres, limited access to computers, unstable electricity and internet connectivity, lack of computer skills and training, and the barriers to access computers. These challenges may have caused frustration and dissatisfaction among health workers.

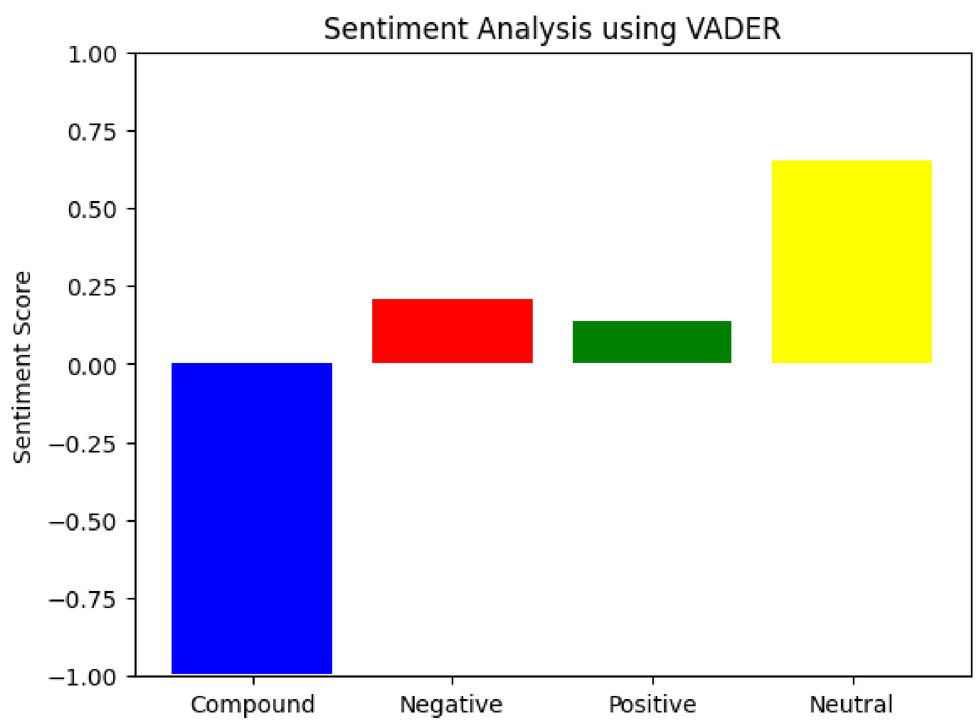

Figure1. Sentiment analysis using Vader score

3.4.Word Cloud Analysis

The word cloud (fig2) generated from the text suggests that the most frequent topics mentioned in the text are related to "software," "lack," "electricity," "connection," "mastery," "obstacles," and "training "The size of the word in the word cloud represents the frequency of occurrence of the word in the text. From the word cloud, we can see that the words "software" and "lack" are the most frequently mentioned, followed by "electricity," "connection," "mastery," "obstacles," and "training." This suggests that the text may be discussing issues related to the lack of software and training centres for health workers, the lack of computers and electricity in health centres and barriers to access to computers. The word "mastery" also appears frequently, indicating that the text may discuss the mastery level of basic computer skills and software among health workers. The word "training" also suggests that the text may be discussing the need for training programs to improve the computer skills of health workers.

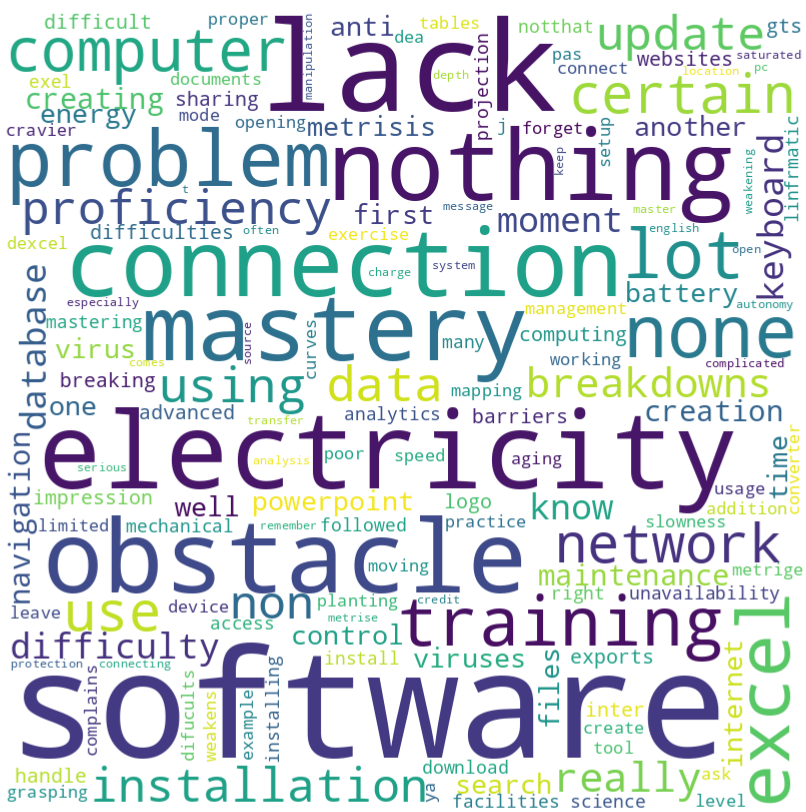

Figure2. Visual Representation of Word Frequency

4. Discussion

According to our study, the level of computer proficiency among healthcare workers in Guinea remains a concerning issue. The study found that only 22.5% of healthcare workers reported using computers in their work, with usage varying by sex and profession. General practitioners and specialists were the most frequent users, along with those working in health centers and prefectural hospitals[9]. The study also identified various obstacles to computer use and implementation in healthcare, including clinicians' concerns about disrupting clinical work and losing clinical autonomy. Additionally, time-consuming tools, tools that do not integrate well into the workflow, tool complexity, and inadequate computer knowledge were frequently cited as barriers [10].

However, the study also found that appropriate training was a significant motivating factor for healthcare workers to use computer tools in clinical practice. This finding aligns with other studies that have emphasized the importance of adequate training and support for healthcare workers in utilising computer tools effectively [11]. The low level of computer proficiency among healthcare workers in Guinea presents a significant challenge to the adoption of digital health tools in the country. Addressing the identified obstacles, such as improving training and support, may help improve computer use among healthcare workers and ultimately improve patient outcomes [12–14].

Although we observed a very positive overall attitude towards the tools among clinicians, none of the available tools is used regularly in daily practice. It appears that there is a significant lack of information and a pedagogical need to help clinicians understand the potential of such computer tools [15]. We observed that the majority of caregivers would like to use the computer for health-related activities. In the van Gils et al series [17], 51.4% of clinicians said they would likely use a diagnostic tool and 29.4% said they would definitely use a diagnostic tool. The attitude towards the computer tool is one of the key characteristics of eventual acceptance [18,19]. Several models of user acceptance have been proposed to further encourage acceptance of tools in medical practice. [19]. In this context, we would like to address the design model of user acceptance and system adaptation. [19]. Another study published in the Front Public Health journal Reports found that the lack of reliable electricity and internet connectivity were significant barriers to health workers' effective use of telemedicine in low- and middle-income countries[20]. This is consistent with the findings of the current survey, which identified a lack of stable electricity and internet connectivity as significant barriers to using computer tools by health workers. Several studies have also highlighted the need for investment in infrastructure, training programs, and resources to support health workers' effective use of computer tools [20–22]. A study published in the JMIR Medical Informatics identified the need for investment in computer training programs for health workers to improve their computer skills and knowledge[23]. Similarly, a study published in the Elsevier Public Health Emergency Collection highlighted the importance of investment in infrastructure, including reliable electricity and internet connectivity, to support health workers' effective use of computer tools [24].

The sentiment analysis of the survey on the mastery of IT tools by health workers revealed a very negative score of -0.992, consistent with the difficulties encountered by health professionals in the use of

IT tools in their work. Work. Previous studies have highlighted technical barriers, a lack of computer skills and training, and concerns about the impact of computer tools on patient care.[24.25]. The findings underscore the need for interventions such as training and supporting health workers to improve their computer skills, correcting technical issues, and improving infrastructure, to address issues and barriers faced by healthcare professionals.

Word cloud analysis suggests that the text discussed is about the use of software and technology in healthcare, focusing on the lack of resources and training for healthcare workers. Several articles in the literature support these findings by highlighting the challenges healthcare professionals face in adopting and using digital health technologies, especially in low-resource settings [27–29]. These results point to the need for further investment in infrastructure, training and support to enable healthcare professionals to effectively use technology in their practice and thus improve the quality and efficiency of healthcare delivery.

5. Conclusion

In conclusion, the low level of computer literacy among healthcare workers in Guinea remains a concern, with only 22.5% having basic computer skills and usage varying by profession, age, and gender. Obstacles to adopting and implementing computer tools in healthcare include lack of training, fear of disruption to clinical workflow, and complexity of tools. However, a positive attitude towards the tools was observed. Despite these challenges, most healthcare workers were willing to use computers for health-related activities.

6. Declarations

6.1 Abbreviations

WHO: World Health Organization

NLTK: Natural Language Toolkit

IQR: Interquartile Range

Word cloud: a graphical representation of word frequency in a text as a weighted list, with larger or more prominent words appearing more frequently in the text.

VADER: Valence Aware Dictionary and Sentiment Reasoner, a tool for sentiment analysis of text

6.2 Conflict of Interest Statement

The authors have no conflict of interests to declare.

6.3 Funding Disclosure

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

6.4 Ethical Considerations

The study was conducted in accordance with ethical principles, and all participants provided informed consent. Throughout the study, confidentiality and anonymity were ensured. The implementation of this study was authorized by the ethics and health research committee, with the approval number 095/CNERS/22.

6.5 Acknowledgements

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6.6 Authors' contribution

The study was conceptualized by ASM, AAT, YS, and OOD, while data collection was supervised by MDD. The data analysis was conducted by ASM, AAT, and NNL. The manuscript was drafted by AAT, BBD, ABN, and GC, and subsequently reviewed and revised by OOD and AJA. All authors have approved the final version of the manuscript for publication.

6.7 Availability of data and materials

The data is available on request, and the Python code used for the analysis is available to the study authors upon request.

6.8 Consent for publication

The data acquisition process has been respected, and there is no obstacle to the publication of this data.

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