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Conflict exposure and healthcare perceptions: Micro-level evidence from Africa

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Abstract
Although considerable research has examined the impact of violent conflict on health outcomes in Africa—such as undernutrition, child mortality, and maternal mortality—a significant gap remains in understanding how it affects individuals' perceptions of healthcare services and the quality of their interactions with healthcare staff during hospital visits. This study seeks to address that gap by analyzing data from Round 9 of the Afrobarometer survey, conducted across 39 African countries between 2021 and 2023 (n = 53,444). Regression analysis indicates that greater exposure to violent conflict is associated with a lower probability of individuals visiting a healthcare facility in the past year—likely due to fear of victimization, which suppresses health-seeking behavior. Among the subset of respondents who did visit a healthcare facility, further analysis shows that conflict exposure is linked to more negative evaluations of the care they received. Specifically, it increases the likelihood of individuals reporting poor service quality, experiencing disrespect from healthcare staff, and paying bribes to access needed care.

Keywords
Africa, Violent conflict, Healthcare, Perceptions, Service quality

JEL Classifications
D74, F52, I12, I14, I15 I18

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1. Introduction

Sub-Saharan Africa (SSA) faces a host of persistent challenges, including low levels of human development, poor health outcomes, and a high incidence of violent conflict. These issues become particularly stark when SSA is compared with other regions of the world. In 2023, the region recorded a Human Development Index (HDI) score of 0.568—lower than the global average and the lowest among all world regions (UNDP 2025).[2] Of the 26 countries classified as having low human development, 23 were located in SSA. Health indicators further underscore the region's disadvantaged position. According to the World Bank's World Development Indicators (WDI),[3] life expectancy in SSA was 62.6 years in 2023, falling below both the global average of 73.3 and the averages of other regions such as the European Union (81.4), the Arab World (72.4), Latin America and the Caribbean (75.6), and South Asia (71.6).[4] The infant mortality rate in SSA stood at 44.2 per 1,000 live births, significantly higher than the global average of 27.1, as well as regional averages in the European Union (3.1), the Arab World (25.6), Latin America and the Caribbean (13.5), and South Asia (30.2).[5]

In addition to developmental and health challenges, Africa has experienced a troubling rise in violent conflict. Data from the Armed Conflict Location and Event Data Project (Raleigh et al. 2010) reveal that both the incidence and intensity of violence generally increased between 1997 and 2024 (see Figure 1). The year 2024 marked a particularly grim milestone, with approximately 27,000 violent incidents resulting in an estimated 162,000 fatalities—the highest recorded on the continent in the past three decades. Highlighting the devastating impact of violence, the renowned peace and conflict researcher Johan Galtung once said, "Peace is to violence what health is to disease"

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[2] The Human Development Index (HDI) is a composite measure accounting for education, life expectancy, and income. It ranges from 0 to 1, with a value of 1 denoting the highest level of development and 0 the lowest.

[3] To access the World Bank's World Development Indicators (WDI) dataset, visit: https://databank.worldbank.org/source/world-development-indicators

[4] The five countries with the lowest life expectancy in 2023—Nigeria (54.5), Chad (55.1), Lesotho (57.4), Central African Republic (57.4), and South Sudan (57.6)—were all in Sub-Saharan Africa.

[5] The five countries with the highest infant mortality rate in 2023—Somalia (67.8), Niger (67.4), Guinea (61.5), Central Africa Republic (60.4), and Nigeria (60.1)—were all in Sub-Saharan Africa.

(Galtung 2011, p. 3). However, the two elements of this comparison are not entirely separate, as the absence of violence is crucial to both physical and psychological health. As Openshaw (2012, p. 2) succinctly noted, “War is not conducive to good health.”

Indeed, several studies have examined the impact of violent conflict on health outcomes. Using data from 52 African countries, Meierrieks and Schaub (2024) found that terrorism has a significant positive effect on under-five child mortality. While they acknowledged that terrorism can have direct effects, they emphasized that most fatalities occur through indirect mechanisms—primarily rooted in behavioral responses among parents, healthcare workers, and policymakers. For example, travel becomes particularly risky in conflict zones, which may discourage parents from seeking routine medical care for their children. Similarly, doctors and other healthcare professionals may choose to relocate to safer regions. This exodus leads to a shortage of medical personnel where they are most needed, thereby increasing the risk of child mortality. Moreover, violent conflict often forces governments to reallocate public funds toward security and military expenditures. This diversion of resources frequently comes at the expense of essential sectors such as public health, further compounding the negative effects on child survival and overall health outcomes.

In a related study, Schaub (2024) analyzes Afrobarometer survey data from 22 African countries to explore the impact of violent conflict on healthcare-seeking behavior. His findings indicate that exposure to violence erodes trust in government institutions and heightens fear, both of which discourage individuals from seeking medical care. This reduced demand for healthcare services contributes to lower immunization rates and higher infant and child mortality. Similarly, a recent study by De Groot et al. (2025) in South Sudan finds that violent conflict has led to widespread acute malnutrition and elevated under-five child mortality. The authors suggest that key conflict-related mechanisms—such as rising food prices and population displacement—are likely drivers of these adverse health outcomes.

Despite growing evidence on the health impacts of violent conflict, there remains a notable gap in empirical research examining how such exposure affects individuals' perceptions of healthcare services and the quality of their interactions with healthcare staff during hospital visits, particularly in the African context. This study seeks to address that gap by leveraging geocoded data from Round 9 of the Afrobarometer survey, conducted across 39 African countries between 2021 and 2023 (n = 53,444). The analysis proceeds in two steps. In the first step, I examine whether individuals exposed to violent conflict are more or less likely to have visited a hospital or clinic in the past year. In the second step, which focuses on the subsample of respondents who did visit a healthcare facility, I assess how conflict exposure relates to their evaluation of healthcare service quality, specifically in terms of the availability of medicines, waiting times, the condition of facilities, and the presence or absence of medical personnel. I also assess respondents' interactions with healthcare staff. Here, I investigate whether exposure to violent conflict increases the likelihood of experiencing disrespect from healthcare staff and the need to pay bribes to obtain necessary care.

To measure exposure to violent conflict, I use QGIS software to calculate the total number of violent conflict incidents that occurred within a 30-kilometer radius of each respondent's dwelling. This variable is constructed by integrating the geocoded Afrobarometer survey data with conflict event data from the Armed Conflict Location and Event Data Project (ACLED) (Raleigh et al., 2010). To assess respondents' perceptions of healthcare services and the quality of their interactions with healthcare staff, I draw on specific items from the Afrobarometer survey. Healthcare quality is measured using an additive index that combines responses to questions about the frequency with which respondents encountered the unavailability of medicines, absence of doctors, long waiting times, and poor facility conditions during their hospital visits. Disrespect from healthcare staff is measured using a question that asks respondents how often they feel they are treated with respect by healthcare providers. Finally, bribery is assessed through an item that asks about the frequency with which respondents had to pay bribes to healthcare staff to access the care they needed.

The regression analysis reveals a negative correlation between exposure to violent conflict and hospital visits. In other words, the more individuals are exposed to violent conflict, the less likely they are to have visited a healthcare facility in the past year. This decline in health-seeking behavior may be attributed to the destruction of healthcare infrastructure and the displacement of medical personnel—both common consequences of violent conflict. Further analysis shows positive correlations between conflict exposure and (1) negative assessments of healthcare facilities, (2) perceived disrespect from healthcare staff, and (3) incidences of bribery involving healthcare personnel. The poor evaluations of healthcare services likely reflect the strain placed on limited healthcare resources in conflict zones. This strain often manifests in overcrowded facilities, shortages of medical personnel, and insufficient medical supplies, all of which can significantly undermine patients' experiences. Moreover, the increased workload and stress associated with operating in conflict-affected areas may lead to burnout among healthcare staff, which in turn can result in emotional detachment or impatience—behaviors that patients may perceive as disrespectful or rude. Finally, the higher incidence of bribery in these settings may stem from weak governmental oversight and financial instability among healthcare workers, including the irregular payment of salaries, which can incentivize informal or illicit payments.

This study contributes to the broader literature on the relationship between violent conflict and health (e.g., De Groot et al. 2025; David & Eriksson 2025; Meierrieks & Schaub 2024; Schaub 2024; Openshaw 2012). The remainder of this study is organized as follows: Section 2 discusses the trend of violent conflict in Africa. Section 3 reviews the relevant literature and presents the hypotheses. Section 4 introduces the data, describes the variables used in the regression models, and outlines the analytical technique. Section 5 presents and interprets the regression results, while Section 6 summarizes the main findings and concludes the study.

2. Trend of violent conflict in Africa

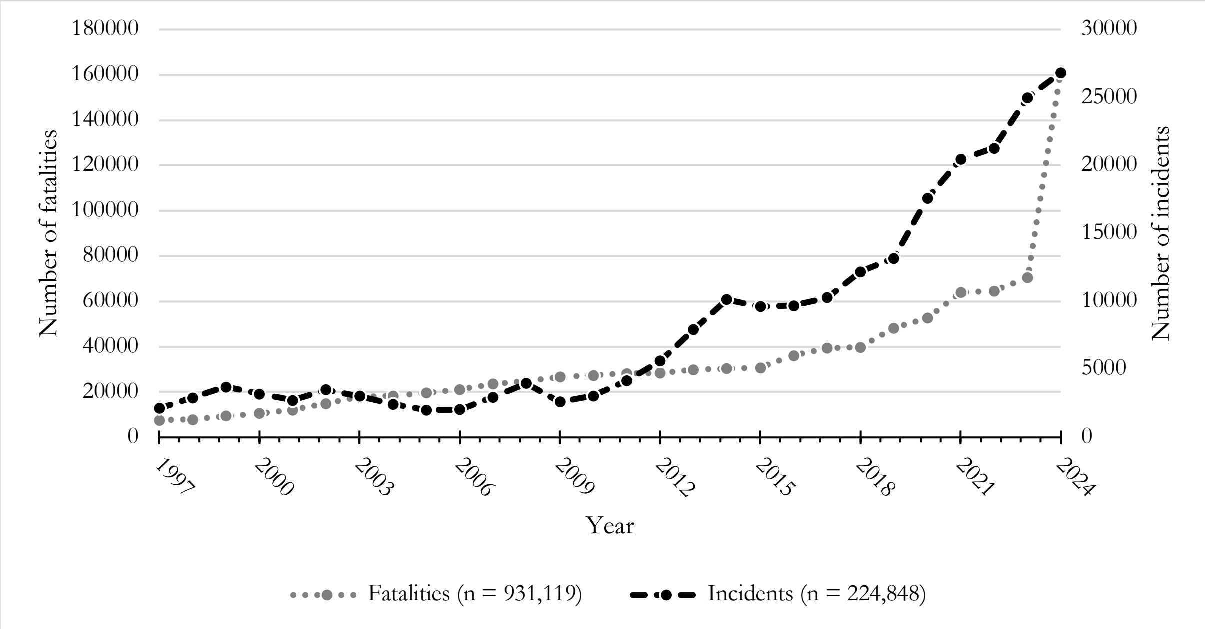

Figure 1: Violent conflicts and associated fatalities in Africa, 1997–2024

Note: The figure visualizes the incidence of violent conflicts in Africa and the associated fatalities from 1997 to 2024. The grey dotted line, which corresponds to the vertical axis on the left, shows the total annual fatalities, while the black dashed line, associated with the vertical axis on the right, shows the total annual number of incidents. The horizontal axis represents the year. Violent conflicts are defined as incidents that fall into one of the following three categories: battles, violence against civilians, and explosions/remote violence. In other words, I exclude events classified as protests, riots, and strategic developments. The data were obtained from the Armed Conflict Location and Event Data Project (ACLED) database.

Figure 1 illustrates the trends in violent conflict and associated fatalities across Africa from 1997 to 2024. Over this 27-year period, the continent experienced a total of 224,848 violent conflict incidents, resulting in 931,119 deaths. Both the incidence and intensity of violent conflict have increased over time, as reflected by the upward trajectories of the two lines in the figure. In 1997, there were 2,183 recorded conflict incidents. By 2024, this number had risen to 26,830—an increase of approximately 1,100 percent. Similarly, the number of conflict-related fatalities grew from 7,647 in 1997 to 161,712 in 2024, representing an increase of roughly 2,000 percent. Notably, 2024 stands out as the most violent year on record, both in terms of the frequency of incidents and the number of fatalities.

A glance at the fatality curve reveals a sharp rise in the number of fatalities between 2023 and 2024. In 2023 alone, 70,514 fatalities were recorded. However, by 2024, this figure had more than doubled (161,712). A closer look at the data shows that six countries—Sudan (15,678), Nigeria

(9,517), Ethiopia (7,512), Burkina Faso (7,485), Somalia (5,541), and the Democratic Republic of Congo (4,155)—recorded the highest number of conflict-related fatalities in 2024. Collectively, these countries accounted for approximately one-third of the total fatalities across the continent that year.

3. Theoretical considerations

Psychological theories such as *Maslach's Burnout Theory* and *Compassion Fatigue Theory* are essential for understanding how exposure to violent conflict shapes individuals' perceptions of healthcare services, the degree of respect they feel is shown to them by healthcare staff during hospital visits, and bribery among healthcare staff. Maslach's burnout theory (MBT) asserts that burnout is not a sudden phenomenon, but rather a gradual process that unfolds over time. It does not arise from brief exposure to stressful work conditions, but instead from prolonged and chronic exposure (Montgomery & Maslach 2019; Maslach & Leiter 2022, 2017, 2016; Maslach et al. 2001; Leiter & Maslach 2016). Several factors can contribute to burnout, including work overload, lack of control (e.g., micromanagement or limited decision-making power), insufficient rewards (e.g., inadequate remuneration or lack of recognition), breakdowns in workplace community (e.g., social isolation, interpersonal conflict, or disrespect), perceived unfairness (e.g., discrimination or favoritism), and value conflicts—particularly when an individual's personal values are at odds with those of their organization (Montgomery et al. 2019; Leiter & Maslach 2004, 1999; Maslach & Leiter 2000). The theory identifies three core dimensions through which burnout is experienced. The first is emotional exhaustion, characterized by feelings of being emotionally depleted and fatigued by work demands. The second is depersonalization, which involves developing a cynical or detached attitude toward the recipients of one's work, often resulting in callous or indifferent behavior. The third is reduced personal accomplishment, where individuals feel ineffective in their roles, experience a deep sense of unfulfillment, and perceive a lack of achievement (Maslach & Leiter 2016, 2000; Maslach 2003; Schaufeli et al. 2009).

Closely related to MBT is Compassion Fatigue Theory (CFT), though the two diverge in several important ways. While MBT emphasizes work overload and institutional stress, CFT focuses more specifically on the emotional toll of prolonged exposure to the trauma and suffering of others. In particular, CFT highlights the psychological and emotional consequences experienced by individuals in caregiving and trauma-exposed professions—such as social workers, healthcare providers, and therapists (Bride et al. 2007; Radey & Figley 2007; Adams et al. 2006; Figley 2002). CFT explains how continuous exposure to others' suffering can lead to emotional exhaustion, reduced empathy, and a gradual desensitization to pain, all of which may impair a caregiver's ability to provide effective support. At its core, the theory rests on several key tenets. It suggests that the very empathy enabling caregivers to connect deeply with those they serve can, paradoxically, render them vulnerable to harm. As Figley (2002, p. 1434) concisely put it, "In our effort to view the world from the perspective of the suffering we suffer." For example, sustained encounters with trauma may lead caregivers to internalize the pain of others, blurring the emotional boundaries between self and patient. Over time, compassion fatigue may accumulate and manifest as diminished empathy, emotional detachment, and growing professional dissatisfaction. Affected individuals may become irritable, disengaged, or increasingly disillusioned with their roles—further compromising their effectiveness and well-being.

Notably, even in the absence of violent conflict, healthcare workers are highly susceptible to burnout and compassion fatigue due to chronic work overload and prolonged exposure to others' trauma and suffering (Dall'Ora et al. 2020; Baugh et al. 2020; Grow et al. 2019; Montgomery et al. 2019; Leiter and Maslach 2009; Pines and Maslach 1978). When healthcare staff operate in conflict zones, the risk of burnout and compassion fatigue are further compounded by exposure to direct threats and victimization (Crawford et al. 2023; Elnakib et al. 2021; Kallström et al. 2021; Elamein et al. 2017; Bernard 2013). This additional layer of stress intensifies the likelihood of emotional exhaustion and disengagement. For instance, Adwi et al. (2025) conducted a study among 78 humanitarian aid workers, most of whom had been engaged in Turkey, finding that their experiences working with displaced individuals made them particularly vulnerable to secondary traumatic stress and compassion fatigue. Elhadi et al. (2020), in a study of 532 hospital and healthcare workers in war-torn Libya, found that 67% of participants reported emotional exhaustion, 47% reported depersonalization, and 22% reported a low sense of personal accomplishment. Furthermore, 57% had experienced verbal abuse, and 18% had suffered physical abuse. Other studies echo these findings. Mette et al. (2020), examining social workers in Germany who served refugees and the homeless, found a positive correlation between demanding work conditions and personal burnout. Similar patterns have been documented among humanitarian health and aid workers operating in emergency settings across diverse contexts, including South Sudan (Strohmeier et al. 2018), Jordan (Eriksson et al. 2013), Greece (Chatzea 2018), Bangladesh (Foo et al. 2023), Uganda (Ager et al. 2012), and along the Thai-Myanmar border (Paw et al. 2025).

Moreover, beyond the immediate loss of life and physical injuries, and the deterioration in the psychological well-being of medical personnel, violent conflict places significant strain on already limited healthcare services in affected areas. It often results in the destruction of health facilities (Jabbour & Fardousi 2022; Omar 2020; Briody et al. 2018; Footer et al. 2018), the death or injury of emergency health workers (Crawford et al. 2023; Kallström et al. 2021; Elamein et al. 2017; Bernard 2013), and the displacement of medical personnel (Meierrieks & Schaub 2024). These disruptions not only reduce the availability of care but also heighten the demand for the remaining healthcare resources. The increased pressure on limited services—particularly from individuals with urgent medical needs—can lead to compromised perceptions of care quality. For example, hospitals may be understaffed due to the displacement of healthcare workers, resulting in long waiting times. The surge in patient numbers may also cause shortages of essential medicines, while the destruction of infrastructure may force the establishment of makeshift clinics with substandard conditions (Tammi et al. 2021; Harrell et al. 2020; Elamein et al. 2017; Fouad et al. 2017). Together, these factors can significantly diminish patients' experiences and influence how they assess the quality of healthcare they receive in conflict zones.

I thus expect that Africans living in conflict-affected areas will have a higher likelihood of encountering emotionally exhausted staff and receiving sub-optimal healthcare. These experiences, in turn, should negatively impact their perceptions of the healthcare system and increase the likelihood that they perceive healthcare workers as rude. These considerations inform the first two hypotheses that this study aims to test:

H1: *Exposure to violent conflict positively correlates with poor perceptions of healthcare services.*

H2*:* *Exposure to violent conflict positively correlates with perceived disrespect by healthcare staff.*

Violent conflicts in Africa have been attributed to a wide range of factors, including ethnoreligious diversity (Tuki 2025, 2024; Basedau et al. 2016, 2011; Posner 2004; Montalvo & Reynal-Querol 2005), poverty (Collier 2008; Collier & Hoeffler 2004), climate change (Eberle & Rohner 2025; McGuirk & Nunn 2025), and physical geography (Herbst 2000), among others. Conflict zones are frequently marked by weak state capacity or the complete absence of government authority. In such contexts, the lack of governance creates favorable conditions for predatory armed groups to emerge and consolidate power, as evidenced in the Nigerian case (Ejiofor 2025; Buba 2023). These groups often establish corrupt and exploitative systems that prioritize their own enrichment over ethical governance. The normalization of unethical behavior in these environments can spill over into critical public sectors, including healthcare.

In the absence of effective government oversight, healthcare workers may be more likely to violate professional norms—for example, by soliciting bribes from patients in exchange for services. Moreover, without a functioning state, healthcare workers may face irregular or nonexistent salary payments (Elnakib et al. 2021; Harrell et al. 2020), which could further incentivize informal or illicit means of financial survival, including bribery. In addition, violent conflict often compels governments to prioritize security-related spending, frequently at the expense of essential sectors such as health (Lang & Vo 2024; Meierrieks & Schaub 2024; Kim 2018). This reallocation of resources may result in poor working conditions and inadequate compensation for healthcare workers, thereby increasing the likelihood of unethical practices such as bribery. Furthermore, conflict-induced scarcity—such as reduced availability of staff, medicines, and equipment, combined with increased demand—creates an environment in which it may be easier for healthcare staff to demand bribes in exchange for treatment (i.e., bribes become a way of jumping very long queues). Additionally, the financial demands placed on patients by healthcare workers may not necessarily be related to their own salaries; rather, they may reflect the need to procure essential medicines and equipment amid limited funding. Collectively, these dynamics illustrate how conflict-induced state weakness can degrade the ethical standards of healthcare delivery.

In light of the preceding discussion, I expect that healthcare workers in conflict zones are likely to experience poorer socioeconomic conditions and a lack of financial security. I also anticipate limited government oversight of healthcare institutions in these areas, which may be reflected in the absence of formal mechanisms for patients to file complaints or hold healthcare providers accountable for unethical behavior. These governance gaps can foster a climate of impunity, where unethical practices—such as the solicitation of bribes—are more likely to occur. Consequently, patients in conflict-affected settings may face a higher likelihood of encountering healthcare workers who demand bribes in exchange for medical services. This forms the basis for the third hypothesis that this study seeks to test:

H3: *Exposure to violent conflict positively correlates with the bribery of healthcare staff in Africa.*

4. Data and methodology

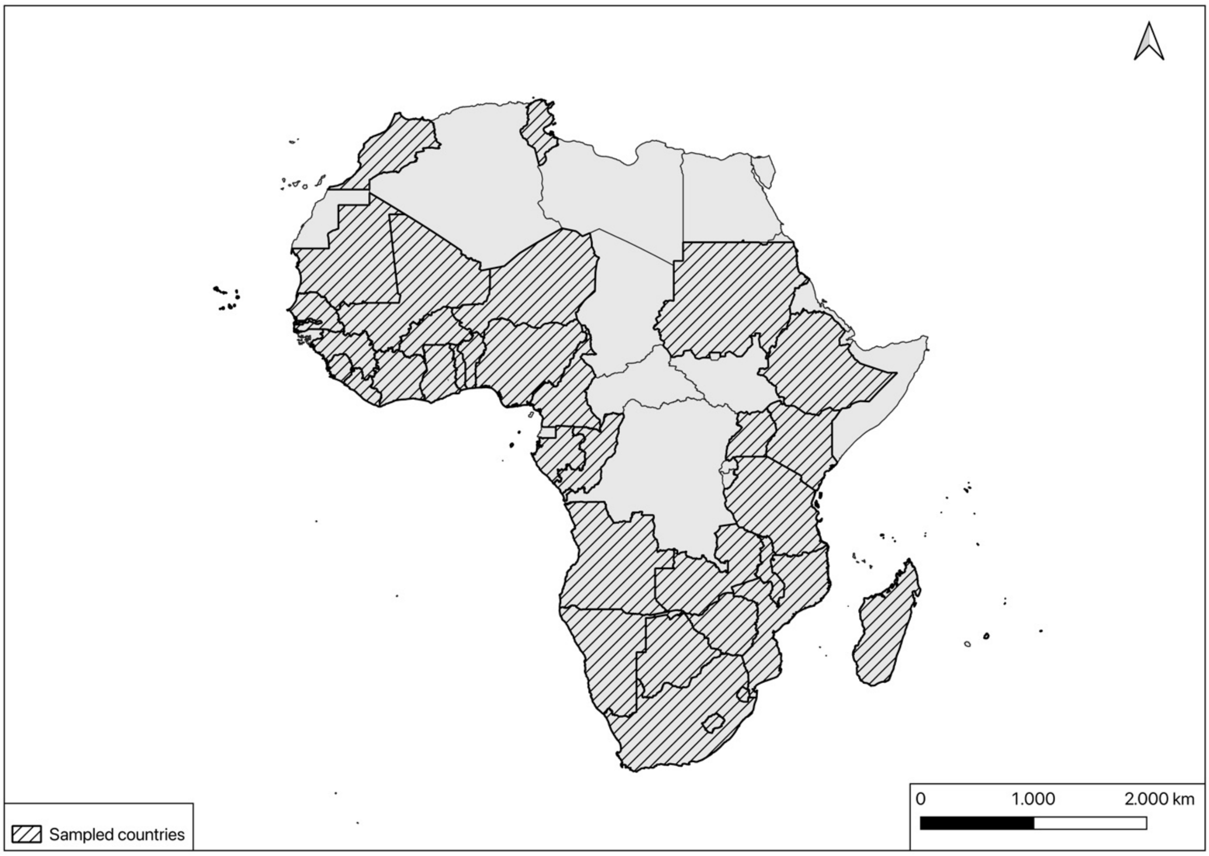

Figure 2: Scope of the Round 9 Afrobarometer data

Note: The figure shows the national boundaries of African countries and highlights the surveyed countries using diagonal lines.

This study uses data from Round 9 of the Afrobarometer survey, conducted between 2021 and 2023 in 39 African countries.[6] Figure 2 illustrates the geographic coverage of the dataset, which includes 53,444 individual observations, with country-level samples ranging from 1,120 to 2,400 respondents. Table A9 in the appendix provides a list of the countries included in the sample along with the number of observations from each. Respondents were evenly split by gender, with a 50:50 ratio of men to women. Because Afrobarometer employs probability-based sampling, the data are nationally representative for each of the countries surveyed.[7]

[6] To access the Afrobarometer dataset and the survey questionnaire, visit https://www.afrobarometer.org/

[7] For more details on the sampling strategy employed by Afrobarometer, visit https://www.afrobarometer.org/surveys-and-methods/sampling/

4.1. Operationalization of the variables

4.1.1. Dependent variables

To measure Africans' perceptions of the quality of healthcare they received, as well as their assessment of their relationship with healthcare staff when they visited a facility, I consider three dependent variables, each of which I discuss below. It is important to note that, before respondents were asked to assess the quality of healthcare services they received during visits, they were first asked a filter question—i.e., whether they had visited a clinic or hospital during the past year. Only the subsample of respondents who answered this question in the affirmative were asked the subsequent questions from which I derived the main dependent variables. 58% of the respondents had visited a facility during the past year, while the remaining 42% had not. I used this item to construct a variable—*Contacted hospital*—which is coded as 1 if a respondent visited a hospital and 0 otherwise.

The first dependent variable—*Poor healthcare index*—is an additive indicator that captures respondents' assessment of the quality of care they received during their visit across four different dimensions. Specifically, the index was derived from the question:

> And have you encountered any of these problems with a public clinic or hospital during the past twelve months:
> (a) Lack of medicines or other supplies
> (b) Absence of doctors or other medical personnel
> (c) Long waiting time
> (d) Poor conditions of facilities

The responses to each item were measured on a scale with four ordinal categories, ranging from "0 = Never" to "3 = Often." I treated "Don't know" and "Refused to answer" responses as missing observations. This rule was applied to all variables derived from the Afrobarometer survey. I summed the ordinal values assigned to the responses across the four items to create the index ranging from 0 to 12, with higher scores denoting poorer assessment of healthcare services. The four items yielded a Cronbach's alpha of 0.74, indicating strong internal reliability.

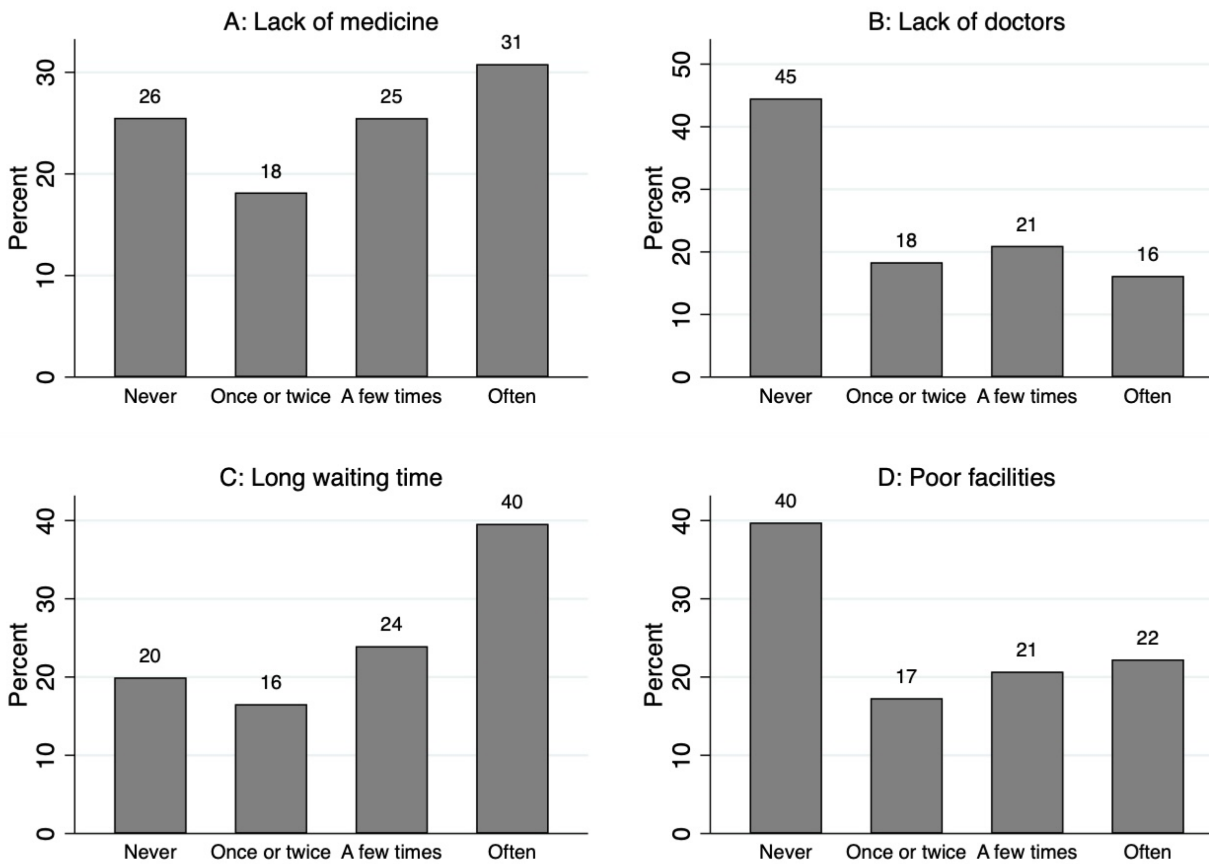

Figure 3: Perceptions among Africans regarding the quality of healthcare received in the past year

Note: This figure presents responses to four questions about the quality of healthcare respondents received in the past year. Panel A displays the frequency with which respondents were unable to access medicine. Panel B shows how often they encountered the absence of doctors at the hospital. Panels C and D illustrate the frequency of long waiting times and the poor condition of hospital facilities, respectively. The horizontal axis indicates the frequencies, while the vertical axis represents the percentage of respondents corresponding to each frequency. The figure is based on survey data from Round 9 of the Afrobarometer survey, conducted across 39 African countries from 2021 to 2023.

Figure 3 presents a bar chart visualizing responses to the four survey questions that comprise the index. The results highlight widespread challenges in healthcare service delivery across the continent. Specifically, 74% of respondents reported experiencing a lack of medicine during at least one hospital visit, 55% encountered a shortage of personnel, and 80% reported facing long waiting times. Additionally, 60% noted experiencing poor facility conditions during their visits.

The second and third dependent variables—*Respectful staff* and *Bribed staff*—shift the focus to the quality of interaction between patients and healthcare personnel during hospital visits. *Respectful staff* captures respondents' perceptions of the respect they received from hospital staff.

Specifically, respondents were asked: "In general, when dealing with health workers and clinic or hospital staff, how much do you feel they treat you with respect?" Responses were recorded on a four-point ordinal scale ranging from "0 = Not at all" to "3 = A lot." *Bribed staff* measures the frequency with which respondents had to pay a bribe to access healthcare services. They were asked: "How often, if ever, did you have to pay a bribe, give a gift, or do a favor for a health worker or clinic or hospital staff in order to get the medical care or services you needed?" Responses were also measured on a four-point ordinal scale, ranging from "0 = Never" to "3 = Often."

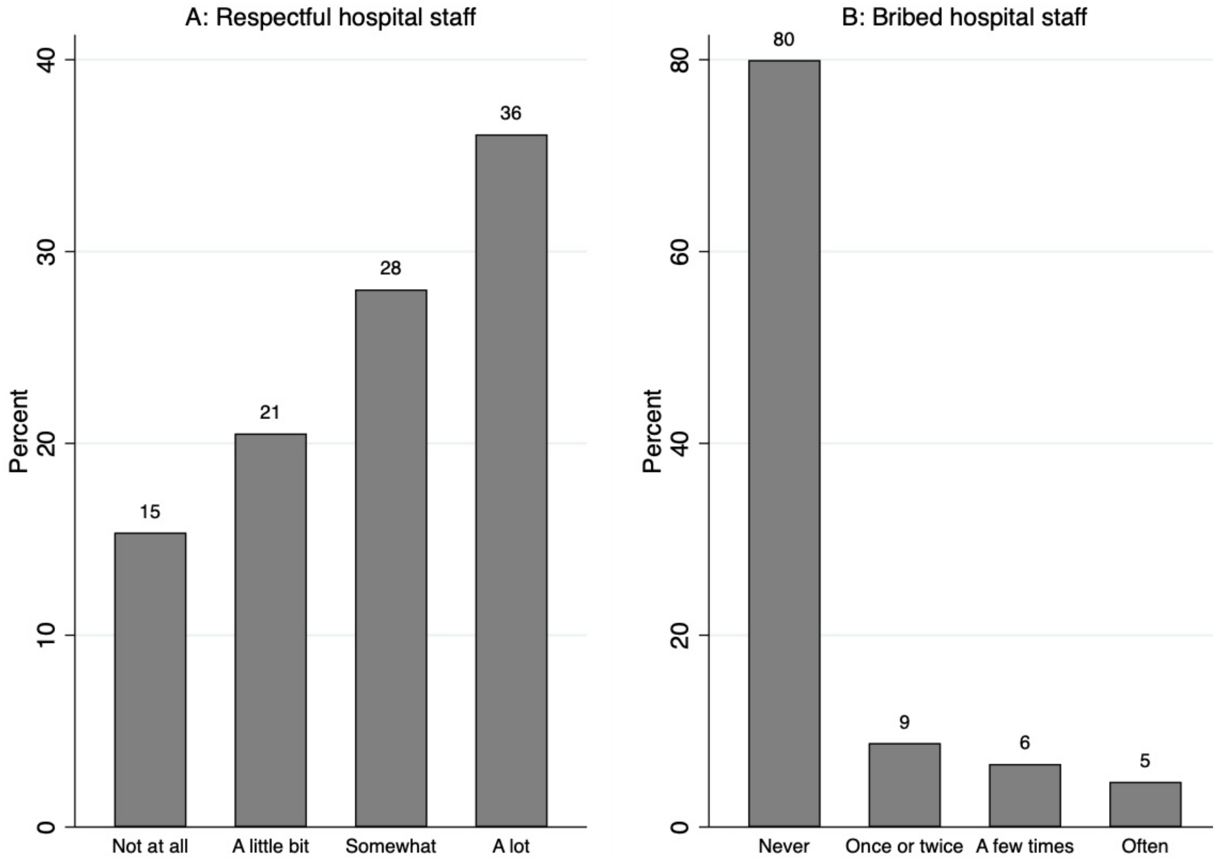

Figure 4: Africans' perceptions of respect from healthcare staff and their experiences with paying bribes to access healthcare services

Note: Panel A illustrates respondents' assessments of the level of respect they received from healthcare staff during visits, while Panel B shows how frequently they reported having to bribe staff to obtain needed healthcare services. The horizontal axis in both panels displays the response categories, and the vertical axis indicates the percentage of respondents in each category. The figure is based on data from Round 9 of the Afrobarometer survey, conducted across 39 African countries between 2021 and 2023.

Figure 4 presents a bar chart illustrating the second and third dependent variables. Panel A shows that 15% of African adults reported receiving no respect from staff during their visits, while 36% felt they were treated with a lot of respect. Panel B reveals that 80% of respondents said they had never paid a bribe to staff to access healthcare services, whereas 20% admitted to having done so at least once.

4.1.2. Explanatory variable

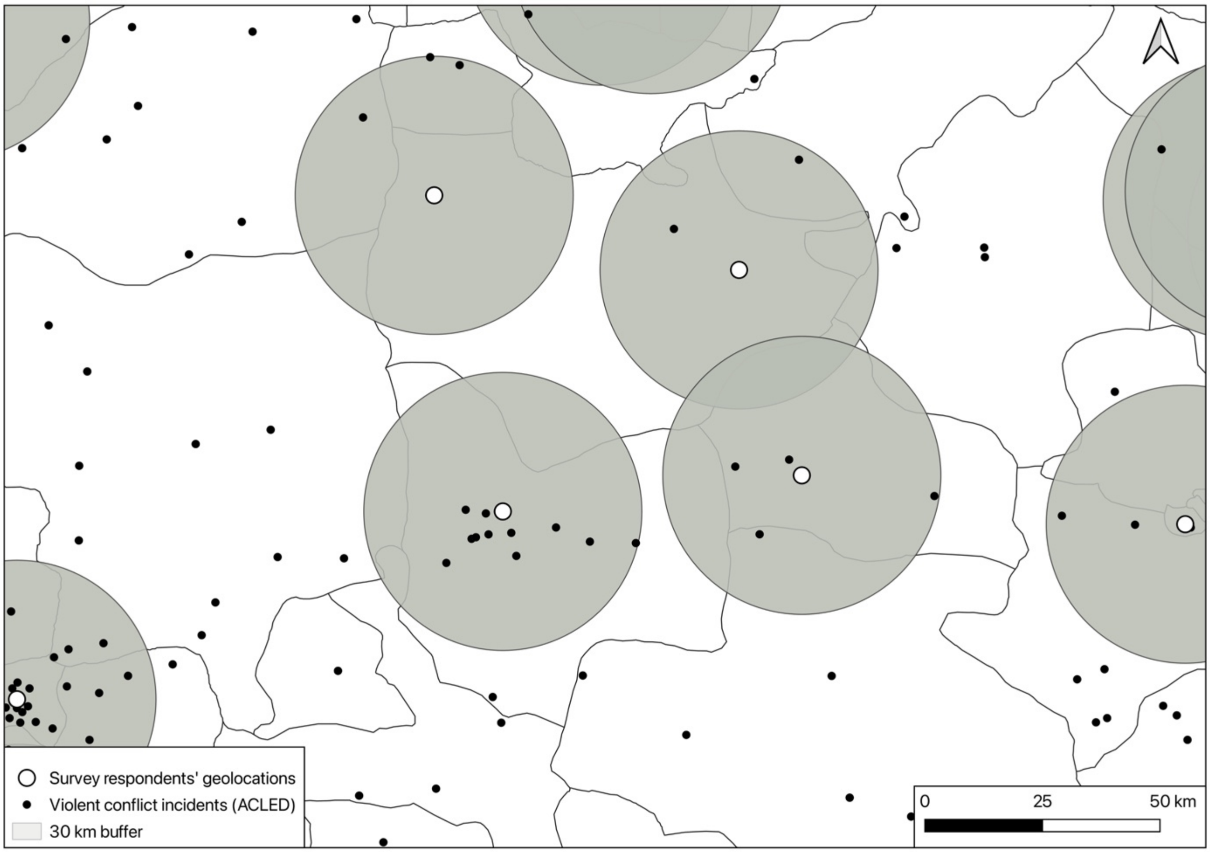

Figure 5: Measuring exposure to violent conflict

Note: The figure visualizes the geolocations of survey respondents, 30 km buffers around their dwellings, the locations of violent conflict incidents, and the admin2 boundaries of the countries in which they reside.

The explanatory variable—*Violent conflict*—measures the cumulative number of violent conflict incidents that occurred within a 30 km radius of each respondent's geolocation, from 1997 up to one year prior to the survey date (see Figure 5). For example, for surveys conducted in 2023, the variable reflects conflict incidents occurring between 1997 and 2022. This lagged structure is intended to mitigate potential reverse causality, as present-day perceptions cannot influence past exposure to violent conflict. I used 1997 as the start year because ACLED data is only available from that point onward. I measured conflict exposure using a 30 km buffer, as violence often has spillover effects that extend beyond its immediate location. This broader radius also helps capture the potential influence of social networks and mobility. For example, respondents may travel for work, maintain close ties with friends and family, or participate in economic and social activities outside their immediate place of residence. Nevertheless, to ensure the results are not sensitive to the choice of buffer size, I constructed alternative versions of the explanatory variable using buffers with radii of 20 km and 10 km. These alternative specifications were then used to conduct a robustness check.

Rather than using administrative boundaries to measure conflict exposure, this study employs spatial buffers around respondents' locations. This approach offers several advantages. First, it avoids reliance on administrative units, which in many African contexts are poorly defined and do not always align with the geographic spread of violence—especially where conflicts are transnational in nature. Second, using buffers introduces greater variation in the conflict exposure measure, since each buffer corresponds to a unique spatial area based on the respondent's location. In contrast, using administrative units (e.g., states or municipalities) would require assigning the same conflict exposure value to all individuals within a given boundary, assuming uniform exposure—an assumption that may be unrealistic.

Using data from the Armed Conflict Location and Event Data Project (ACLED) (Raleigh et al. 2010), I define violent conflict as any incident classified under one of three categories: battles, violence against civilians, and explosions/remote violence. This operationalization excludes less violent events such as protests, riots, and strategic developments, thereby focusing specifically on episodes of severe violence. I adopt a long-term perspective on conflict exposure, as my primary interest lies in understanding the cumulative impact of violent conflict over time. Prior research has shown that the effects of violent conflict often persist well beyond the immediate aftermath (e.g., Tuki 2025a, 2024a; Boggiano 2024; Hong and Kang 2017). Moreover, measuring conflict exposure over a longer timeframe reduces the risk of selection bias that can arise from focusing on an unrepresentative period. Short-term studies may capture atypical moments—such as temporary lulls or surges in violence—that do not accurately reflect the broader conflict environment.

In the sample, 73% of respondents had at least one violent conflict incident within a 30 km radius of their dwelling. 48% had 10 or more incidents, while 23% had at least 50 incidents within this buffer zone. I measured conflict exposure using a count of conflict incidents rather than a dummy variable, as this approach allows for differentiation between areas with low and high levels of conflict. A count variable preserves more detailed information about the frequency of incidents, enabling a more nuanced and accurate analysis. In contrast, a dummy variable treats all levels of conflict exposure equally—regardless of whether there was one incident or many—thereby masking important variation in the intensity of exposure.

Notably, I standardized the conflict exposure variable before using it in the regression model. This was done by subtracting the mean from each original value and dividing the result by the standard deviation. This transformation ensures that the variables have a mean of 0 and a standard deviation of 1, placing them on a common scale and facilitating more meaningful comparisons.

4.1.3. Control variables

I included some control variables in the regression model, including poverty, educational attainment, and respondents' demographic characteristics. Educational attainment is measured on a ten-point ordinal scale ranging from "0 = No formal education" to "9 = Post-graduate." Following Mattes et al. (2002), poverty is measured using an additive index that captures the frequency with which respondents and members of their households went without basic necessities—such as food, water, cooking fuel, and income—over the past year. Responses to each item were recorded on a five-point ordinal scale ranging from "0 = Never" to "4 = Always." The index was constructed by summing the ordinal values across the four items. The resulting index, which ranges from 0 to 16, yielded a Cronbach's alpha of 0.72, indicating strong internal reliability. Gender is coded as 1 for female and 0 for male, and age is measured in years.

4.2. Analytical technique

To analyze the relationship between exposure to violent conflict, Africans' perceptions of healthcare quality, and the amount of respect accorded to them during hospital visits, I consider a model of the following general form:

$$\gamma_i = \alpha_0 + \alpha_1 Violent\ conflict_i + \alpha_2 \varphi'_i + \mu_i \qquad (1)$$

In this equation, γ_i is the dependent variable which may represent Respondent $i's$ visit to a healthcare facility during the past year, their assessment of the quality of healthcare they received during their hospital visit, their assessment of the level of respect accorded to them by hospital staff, or the frequency with which they paid a bribe to access healthcare services; φ'_i is a vector of control variables discussed earlier; α_0 is the intercept; α_1 and α_2 denote the coefficients of the explanatory and control variables, respectively, while μ_i is the error term. The models were estimated using a range of techniques, including the Linear Probability Model (LPM), Ordinary Least Squares (OLS) regression, and Ordered Logit (Ologit) regression.

The choice of estimation method was determined by the nature of the dependent variable. For dependent variables measured on a binary scale, I employed LPM regression, which has the advantage of producing easily interpretable coefficients that can be read as probabilities. When the dependent variable had multiple categories—such as the index measuring healthcare quality—I treated it as a continuous variable and used OLS regression. This approach is appropriate for additive indices with several levels of variation. For dependent variables with a small number of ordinal categories, I used Ordered Logit regression. This method is particularly useful for estimating the relationship between the treatment variable and each ordered category of the outcome, providing more nuanced insight than models that treat ordinal outcomes as continuous. In some of the regression models, I include fixed effects for the country in which respondents reside. Country fixed effects account for time-invariant characteristics—such as colonial history, physical geography, and cultural norms—that may be unique to each country and influence the outcome of interest.

Table A1 in the appendix reports the summary statistics of the variables used to estimate the regression model.

5. Results and discussion

Table 1: Regressing contact with a hospital and perceptions of healthcare quality on exposure to violent conflict

Dependent variables:						
	Contacted hospital			**Poor healthcare index**		
	(1) LPM	**(2) LPM**	**(3) LPM**	**(4) OLS**	**(5) OLS**	**(6) OLS**
Violent conflict$^{\sigma}$	-0.034***	-0.031***	-0.015***	0.22***	0.117***	0.075***
	(0.002)	(0.002)	(0.002)	(0.023)	(0.022)	(0.024)
Constant	0.577***	0.486***	0.415***	5.8***	4.22***	6.115***
	(0.002)	(0.009)	(0.017)	(0.02)	(0.085)	(0.166)
Control variables	No	Yes	Yes	No	Yes	Yes
Country Fixed effects	No	No	Yes	No	No	Yes
Observations	53405	52927	52927	30396	30161	30161
R-squared	0.005	0.014	0.081	0.003	0.069	0.177
AIC statistic	75982.76	74803.66	71149.33	162070.8	158722	155085.8
BIC statistic	76000.53	74856.92	71539.9	162087.5	158771.9	155451.7

Note: σ indicates that a variable is standardized. Violent conflict is measured using a radius of 30 km. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Models 1, 2, and 3 are estimated using linear probability model (LPM), while Models 4, 5, and 6 are estimated using ordinary least squares (OLS) regression. The dependent variable in Models 1 to 3, which is measured on a binary scale, indicates whether or not respondents had contact with a clinic or hospital in the past year. The dependent variable in Models 4 to 6 is an additive index ranging from 0 to 12, which measures respondents' assessments of the quality of healthcare they received when they visited a clinic or hospital. Control variables include poverty, educational level, age and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted between 2021 and 2023 across 39 African countries.

I analyze the data using a two-step approach. In the first step, I assess how exposure to violent conflict relates to the likelihood of visiting a hospital—that is, whether experiencing violent conflict makes individuals more or less likely to seek healthcare. In the second step, I examine the relationship between violent conflict and the quality of healthcare services received during hospital visits. This quality is measured through an index that captures factors such as the presence of doctors, waiting times, availability of medicines, and the condition of hospital infrastructure. I also examine the relationship between exposure to violent conflict and the quality of respondents' interactions with healthcare staff—specifically, the level of respect they reported receiving during hospital visits and whether they had to pay a bribe to access the healthcare services they needed.

Table 1 presents the results of regression models corresponding to the first step of the analysis. Models 1 to 3 focus specifically on hospital visits. I estimated these models using the Linear Probability Model (LPM) because the dependent variable is a binary indicator coded as 1 if respondents visited a hospital or clinic, and 0 if they did not. In Model 1, which includes only the violent conflict variable, the coefficient is negative and statistically significant at the 1% level. Specifically, a one–standard deviation increase in exposure to violent conflict is associated with a 3.4 percentage point decrease in the likelihood of seeking healthcare. This suggests that greater exposure to violent conflict reduces the probability that individuals visited a hospital. In Model 2, which includes additional control variables, the coefficient on violent conflict decreases slightly in magnitude but remains negative and statistically significant at the 1% level. Model 3 introduces country fixed effects; although the coefficient is further reduced to about half its original size, it remains negative and statistically significant at the 1% level. The negative association between conflict exposure and health-seeking behavior observed in Africa is consistent with findings from studies conducted in Syria (Elsafti et al. 2016), Palestine (Majaj et al. 2013), Afghanistan (Carthaigh et al. 2015), Democratic Republic of Congo (Herp et al. 2003), and the Philippines (Molina 2020).

A plausible explanation for the negative correlation between violent conflict and hospital visits is that individuals living in conflict zones often face significant mobility restrictions due to insecurity. In other words, traveling to healthcare facilities can be dangerous, leading people to prioritize their personal safety over seeking medical care. Additionally, violent conflict frequently results in the destruction of healthcare infrastructure, including hospitals and clinics. It may also cause the displacement of healthcare workers, who might be unwilling to risk their lives working in these high-risk areas. Furthermore, conflict often disrupts livelihoods and drives people into poverty, making it harder for them to afford healthcare services.

Interestingly, the survey instrument included a question directed at respondents who had contacted a facility, asking about their ease of accessing healthcare services. Specifically, they were asked: “How easy or difficult was it to obtain the medical care or services you needed?” Responses were recorded on a four-point ordinal scale, ranging from “1 = Very easy” to “4 = Very difficult.” To explore this potential mechanism, I regressed this variable on exposure to violent conflict. The results indicate that greater exposure to violent conflict is associated with an increased likelihood of respondents reporting greater difficulty in accessing healthcare. These findings are presented in Table A2 of the appendix. Additionally, Figures A1 and A2, also in the appendix, visualize the predicted probabilities from these regression results, and illustrate respondents' reported ease of accessing healthcare using a simple bar chart.

It is also important to note that the negative correlation between violent conflict and prior hospital visits does not necessarily indicate a lower need for healthcare services. On the contrary, individuals exposed to conflict may have a greater need for medical care, suggesting that the reported estimates could be conservative. For example, exposure to violence can result in physical injuries and psychological trauma, both of which require medical attention. In addition, conflict often disrupts access to essential resources such as food and clean water, and leads to displacement and overcrowding. These conditions can contribute to poor hygiene, food insecurity, and undernutrition—all of which negatively affect health and may increase the demand for healthcare services.

Models 4 to 6 shift the focus of the analysis to perceptions of healthcare quality. I estimated these models using OLS because the dependent variable is an index with multiple categories. Notably, these models have fewer observations, as they are based on the subset of respondents who visited a hospital. In Model 4, which includes only violent conflict as a predictor, the coefficient is positive and statistically significant at the 1% level. Specifically, a 1-standard deviation increase in violent conflict is associated with an increase in the poor healthcare index of 22 percentage points. This result, which supports Hypothesis 1, suggests that the more Africans are exposed to violent conflict, the more likely they are to assess the quality of healthcare they received poorly. When control variables are added in Model 5, the coefficient's magnitude decreases to about half its original size but remains positive and significant at the 1% level. In Model 6, which includes country fixed effects, the coefficient declines further but continues to be positive and statistically significant. A plausible explanation for the positive correlation between violent conflict and poor assessments of healthcare quality is that violence often leads to the destruction of healthcare facilities. This destruction can result in reduced availability of services, overcrowding in the remaining facilities, and the use of makeshift treatment centers (Jabbour & Fardousi 2022; Tammi et al. 2021; Harrell et al. 2020; Elamein et al. 2017; Fouad et al. 2017)—all of which can negatively impact patients' experiences.

It is also possible that respondents' poor evaluations of healthcare facilities are not solely driven by the intrinsic "quality" of care. In other words, the quality itself might remain unchanged, but increased demand caused by conflict could overwhelm these facilities, which may not have been designed to handle such a surge in patients. Furthermore, the nature of people's healthcare needs in conflict zones is likely more complex. As a result, even if facility capacity remains the same, patient satisfaction could still decline due to unmet expectations and the inability of facilities to address these more complex demands.

Notably, the results reported in Table 1 remain consistent when I estimate alternative models that restrict the sample to individuals who experienced at least one conflict incident within a 30 km radius of their dwellings. Table A3 in the appendix reports these results. Additionally, the results are robust to the use of alternative versions of the explanatory variable, in which conflict exposure is measured using buffers with radii of 20 km and 10 km (see Tables A5 and A6 in the appendix).

Next, I turn to respondents' evaluations of their interactions with healthcare staff during hospital visits. Specifically, I assess whether individuals living in conflict-affected areas are more likely to report being treated with disrespect by healthcare workers or to have paid a bribe to receive medical care. Models 1 to 3 focus on perceived respect. These models are estimated using ordered logit regression (Ologit), as the dependent variable is ordinal with only a few categories. In Model 1, which includes only exposure to violent conflict, the coefficient is negative and statistically significant at the 1% level. This result is consistent with Hypothesis 2, which posits that greater exposure to violent conflict is associated with a higher likelihood of reporting disrespectful treatment by hospital staff. Model 2 shows that this negative association remains robust after including control variables, while Model 3 confirms that the relationship holds even when country fixed effects are added.

Table 2: Ordered logit models regressing perceived respect from healthcare staff and bribery on exposure to violent conflict

Dependent variables:	**Respectful staff**			**Bribed staff**		
	(1) Ologit	**(2) Ologit**	**(3) Ologit**	**(4) Ologit**	**(5) Ologit**	**(6) Ologit**
Violent conflict$^{\sigma}$	-0.062***	-0.024**	-0.028**	0.182***	0.173***	0.048***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.014)	(0.016)
Intercept 1	-1.705***	-1.809***	-1.412***	1.381***	1.001***	0.72***
	(0.016)	(0.048)	(0.083)	(0.014)	(0.063)	(0.112)
Intercept 2	-0.579***	-0.668***	-0.237***	2.062***	1.691***	1.478***
	(0.012)	(0.046)	(0.082)	(0.018)	(0.064)	(0.112)
Intercept 3	0.574***	0.506***	1.003***	3.009***	2.641***	2.48***
	(0.012)	(0.046)	(0.082)	(0.027)	(0.067)	(0.114)
Control variables	No	Yes	Yes	No	Yes	Yes
Country Fixed effects	No	No	Yes	No	No	Yes
Observations	30761	30509	30509	30784	30534	30534
Pseudo R^2	0.00	0.009	0.033	0.004	0.014	0.087
Log pseudolikelihood	-41112.39	-40429.799	-39452.805	-21920.215	-21517.15	-19931.101
AIC statistic	82232.78	80875.6	78997.61	43848.43	43050.3	39954.2
BIC statistic	82266.12	80942.21	79380.6	43881.77	43116.91	40337.23

Note: σ indicates that a variable is standardized. Violent conflict is measured using a radius of 30 km. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10. All models are estimated using ordered logit (Ologit) regression. The dependent variable in Models 1 to 3, which is measured on a scale with four ordinal categories, captures respondents' assessment of the level of respect with which they were treated by staff when they visited the facility. The dependent variable in Models 4 to 6, which is also measured on a scale with four ordinal categories, captures the frequency with which respondents paid a bribe to staff in order to receive the medical care they needed. Control variables include poverty, educational level, and respondents' age and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted between 2021 and 2023 across 39 African countries.

A plausible explanation for why hospital staff in conflict zones treat patients with disrespect lies in the combined effects of overwork, exhaustion, and psychological burnout. Violent conflict often leads to the displacement of healthcare workers, leaving a limited number of staff to care for a growing population of patients in urgent need. This overwhelming burden can place immense strain on remaining personnel, leading to impatience, emotional detachment, and fatigue (Cameron et al. 2024; Crawford et al. 2023; Omar 2020; Elnakib et al. 2021; Eriksson et al. 2009)—behaviors that patients may interpret as rudeness or disrespect. Moreover, healthcare workers themselves are not immune to the psychological toll of conflict. The constant threat of violence, exposure to traumatic events, and personal loss can severely affect their mental well-being and interpersonal interactions (Paw et al. 2025; Foo et al. 2023; Lafta & Falah 2019; Strohmeier et al. 2018; Ager et al. 2012). In addition, conflict zones often suffer from weakened state capacity, resulting in poor oversight and limited mechanisms for accountability within the healthcare system. With minimal supervision and few avenues for patients to report mistreatment, professional standards may deteriorate, further contributing to disrespectful behavior by medical personnel. Conversely, perceptions of disrespect might have more to do with patients than healthcare staff. For instance, patients visiting clinics in conflict zones are more likely to be desperate and impatient—particularly when in need of urgent care and faced with overburdened healthcare staff. This heightened impatience may lead them to perceive staff as rude, regardless of the staff's actual behavior.

Models 4 to 6 shift the focus of the analysis to the issue of bribery in healthcare. In Model 4, which includes only the violent conflict variable, the coefficient is positive and statistically significant at the 1% level. This result, which supports Hypothesis 3, indicates that greater exposure to violent conflict is associated with a higher likelihood that individuals paid a bribe to healthcare workers to access medical services. Model 5 shows that this positive relationship remains robust even after including additional control variables, while Model 6 confirms that the result persists when country fixed effects are included. The mechanisms underlying these findings may be similar to those discussed in Models 1 to 3. In the absence of strong government oversight, this heightened demand for healthcare in conflict zones may create opportunities for healthcare workers to exploit patients by soliciting bribes. Additionally, conflict often disrupts the functioning of the state, including the regular payment of public sector wages or the underpayment of crisis workers (Elnakib et al. 2021; Harrell et al. 2020). As a result, financial insecurity among healthcare workers may further incentivize the extraction of informal payments from patients.

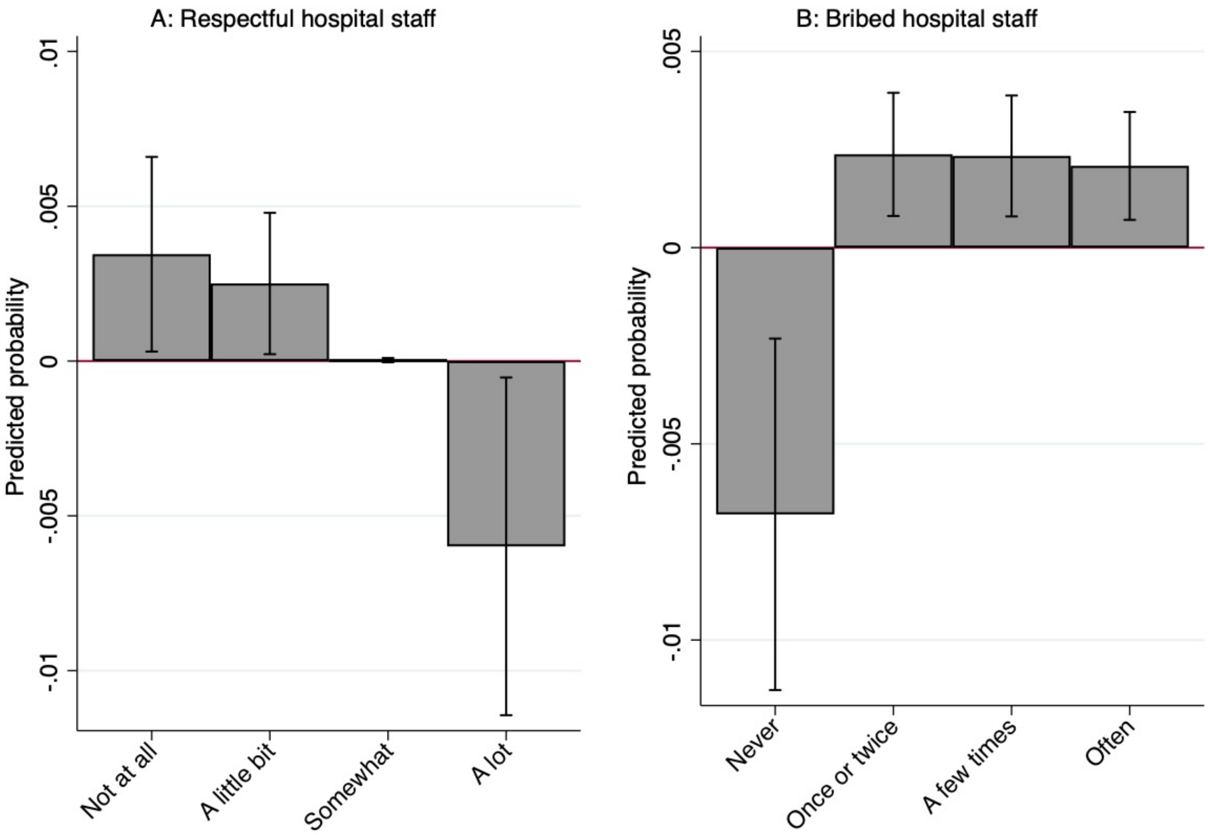

Figure 6: Predicted probabilities showing the associations between conflict exposure, perceived respect from healthcare staff, and bribery

Note: Panel A, based on Model 3 in Table 2, shows the association between violent conflict and each category of the first dependent variable, which measures respondents' assessment of the level of respect with which they were treated by hospital staff. Panel B, based on Model 6 in Table 2, shows the association between violent conflict and the second dependent variable, which measures the frequency with which respondents paid a bribe to hospital staff in order to receive medical care. The horizontal axis shows the different levels of both dependent variables, while the vertical axis shows the predicted probabilities. Confidence intervals are set at the 95% level. The figure is based on survey data from Round 9 of the Afrobarometer survey, conducted across 39 African countries from 2021 to 2023.

To better illustrate the magnitude of the associations between violent conflict, perceived respect from healthcare staff, and bribery, I plotted the predicted probabilities based on the full models—specifically, Models 3 and 6 in Table 2—in Figure 6. This step is especially important because interpreting coefficients from Ologit models is less intuitive compared to LPM or OLS models. Panel A focuses on respondents' perceptions of respect. A glance at the figure reveals that the association between conflict exposure and perceived respect is strongest in the "A lot" category of the dependent variable. Notably, violent conflict shows a negative association only with this response category. Specifically, a 1-standard deviation increase in conflict exposure is associated with a 0.6 percentage point decrease in the probability that respondents report being treated with

"A lot" of respect during their hospital visit. At the same time, it increases the probability of respondents selecting the "Not at all" category by 0.3 percentage points, further suggesting a shift toward more negative evaluations of staff behavior as conflict exposure rises.

A closer look at Panel B reveals that the association between violent conflict and bribery of healthcare staff is strongest in the "Never" response category and weakest in the "Often" category. Notably, conflict exposure is negatively associated only with the "Never" category, while the association is positive for all other categories representing varying frequencies of bribery. Specifically, a 1-standard deviation increase in violent conflict is associated with a 0.7 percentage point decrease in the likelihood that respondents report "Never" having paid a bribe to access care. Conversely, it is associated with a 0.2 percentage point increase in the probability of respondents reporting that they "Often" paid a bribe. These results suggest that as exposure to violent conflict increases, so does the likelihood of engaging in informal payments to healthcare providers.

Notably, the results presented in Table 2 remain robust even when the models are re-estimated using a restricted sample consisting only of respondents who experienced at least one conflict incident within a 30 km radius of their dwellings. Table A4 in the appendix reports the results. Additionally, the results are robust to the use of alternative versions of the explanatory variable, in which conflict exposure is measured using buffers with radii of 20 km and 10 km (see Tables A7 and A8 in the appendix).

6. Conclusion

Using survey data from Round 9 of the Afrobarometer survey conducted across 39 African countries between 2021 and 2023, this study examined how exposure to violent conflict relates to perceptions of healthcare quality and the nature of patient interactions with healthcare staff during visits. Regression analyses revealed a consistent pattern: individuals exposed to violent conflict were significantly less likely to visit facilities. This may be due to the risks and insecurity associated with traveling in conflict-affected areas, leading individuals to prioritize personal safety over seeking medical care. Even when individuals in conflict zones do access healthcare, they often face substandard conditions. The analysis showed that greater exposure to violent conflict was associated with a higher likelihood of assessing the quality of healthcare services as poor. Additionally, those exposed to more conflict were more likely to report being treated disrespectfully by healthcare staff and to admit to paying bribes to receive medical attention. These findings suggest that violent conflict not only restricts access to healthcare but also undermines the quality of care and the integrity of patient-staff interactions.

These findings can be attributed to several consequences of violent conflict. First, conflict often leads to the destruction of critical healthcare infrastructure, such as hospitals and clinics. This destruction puts immense pressure on remaining facilities, resulting in reduced service delivery, overcrowding, and the use of makeshift treatment centers, all of which can negatively affect patients' experiences. Second, violent conflict tends to weaken state capacity and disrupt public administration, including oversight of healthcare institutions. Limited supervision can foster an environment where unethical practices go unchecked. In addition, conflict can lead to delays or irregularities in the payment of healthcare workers' salaries, pushing some to resort to bribery or other forms of informal compensation. Third, violent conflict frequently drives healthcare professionals to flee unsafe areas, exacerbating staff shortages just as patient needs become more urgent. The remaining personnel are often overwhelmed by the increased workload, which can lead to burnout, emotional detachment, and impatience—behaviors that patients may interpret as disrespect or poor treatment.

The findings of this study shed light on the significant challenges Africans living in conflict-affected areas face when seeking healthcare. The true cost of violent conflict extends far beyond the immediate destruction of infrastructure—such as hospitals and roads—or the direct loss of life from armed clashes. It also includes indirect, yet devastating, consequences such as preventable deaths resulting from the lack of access to healthcare services, the dangers associated with traveling to medical facilities, or substandard treatment caused by healthcare worker neglect or unethical behavior. Although it may seem intuitive to call for a reduction in violence as a broad policy response, meaningful solutions must be context-specific and rooted in a thorough understanding of the underlying causes of conflict. In the African context, these causes are diverse and complex—ranging from climate change and religious extremism to ethnic tensions, identity politics, and weak governance. Nevertheless, targeted interventions can still make a tangible difference. Non-governmental organizations (NGOs) and international agencies, for example, can help improve healthcare quality by supporting the material and psychological well-being of healthcare workers operating in conflict zones. This could involve providing adequate remuneration and access to mental health support such as counseling services. These efforts may help alleviate stress and burnout among healthcare staff, which in turn could enhance the quality of care delivered to patients.

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Appendix

Table A1: Descriptive Statistics

Variable	Total observations	Mean	Standard deviation	Minimum	Maximum
Contacted hospital	53405	0.577	0.494	0	1
Poor healthcare index	30396	5.787	3.485	0	12
Disrespectful staff	30761	1.849	1.076	0	3
Bribed staff	30784	0.36	0.803	0	3
Violent conflict (30 km)	53444	20.419	66.954	0	1154
Violent conflict (30 km)$^{\sigma}$	53444	0	1	-0.331	14.382
Violent conflict (20 km)	53444	39.472	117.675	0	1599
Violent conflict (20 km)$^{\sigma}$	53444	0	1	-0.335	13.253
Violent conflict (10 km)	53444	20.419	66.954	0	1154
Violent conflict (10 km)$^{\sigma}$	53444	0	1	-0.305	16.931
Poverty index	53159	5.68	3.851	0	16
Educational level	53303	3.589	2.271	0	9
Female (Ref: Male)	53444	0.5	0.5	0	1
Age	53384	38.035	15.018	18	112

Note: "Ref" indicates reference category. σ indicates that a variable is standardized.

Table A2: Regressing ease of access to healthcare on exposure violent conflict

Difficulty accessing healthcare	(1)	(2)	(3)
Violent conflict$^{\sigma}$	0.093***	0.07***	0.04***
	(0.009)	(0.01)	(0.011)
Intercept 1	-1.686***	-1.508***	-1.767***
	(0.016)	(0.047)	(0.089)
Intercept 2	0.199***	0.421***	0.24***
	(0.011)	(0.046)	(0.089)
Intercept 3	1.566***	1.825***	1.698***
	(0.015)	(0.048)	(0.089)
Control variables	No	Yes	Yes
Country Fixed effects	No	No	Yes
Observations	30814	30562	30562
Pseudo R^2	0.001	0.014	0.035
Log pseudolikelihood	-40537.928	-39687.81	-38843.35
AIC statistic	81083.86	79391.62	77778.7
BIC statistic	81117.2	79458.24	78161.77

Note: σ indicates that a variable is standardized. Violent conflict is measured using a radius of 30 km. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. All models are estimated using ordered logit (Ologit) regression. The dependent variable, which is measured on a scale with four ordinal categories (1 = Very easy to 4 = Very difficult), captures respondents' assessment of the ease with which they were able to access the healthcare they needed. Control variables include poverty, educational level, and respondents' age and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted between 2021 and 2023 across 39 African countries.

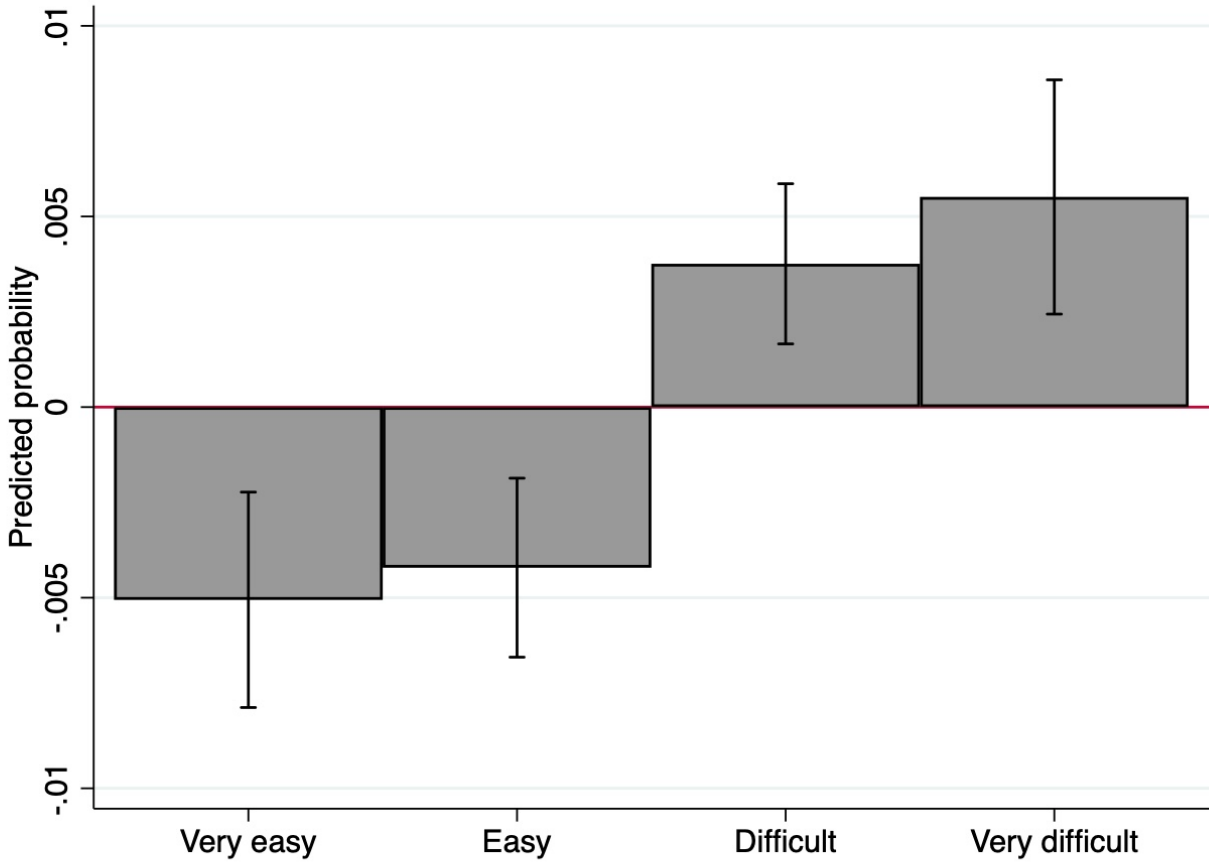

Figure A1: Predicted probabilities showing the association between violent conflict and ease of accessing to healthcare

Note: This figure, based on Model 3 in Table A2, shows the association between violent conflict and each category of the dependent variable, which measures the ease with respondents were able to access healthcare when needed. The horizontal axis shows the different levels of ease, while the vertical axis shows the predicted probabilities. Confidence intervals are set at the 95% level. The figure is based on survey data from Round 9 of the Afrobarometer survey, conducted across 39 African countries between 2021 and 2023.

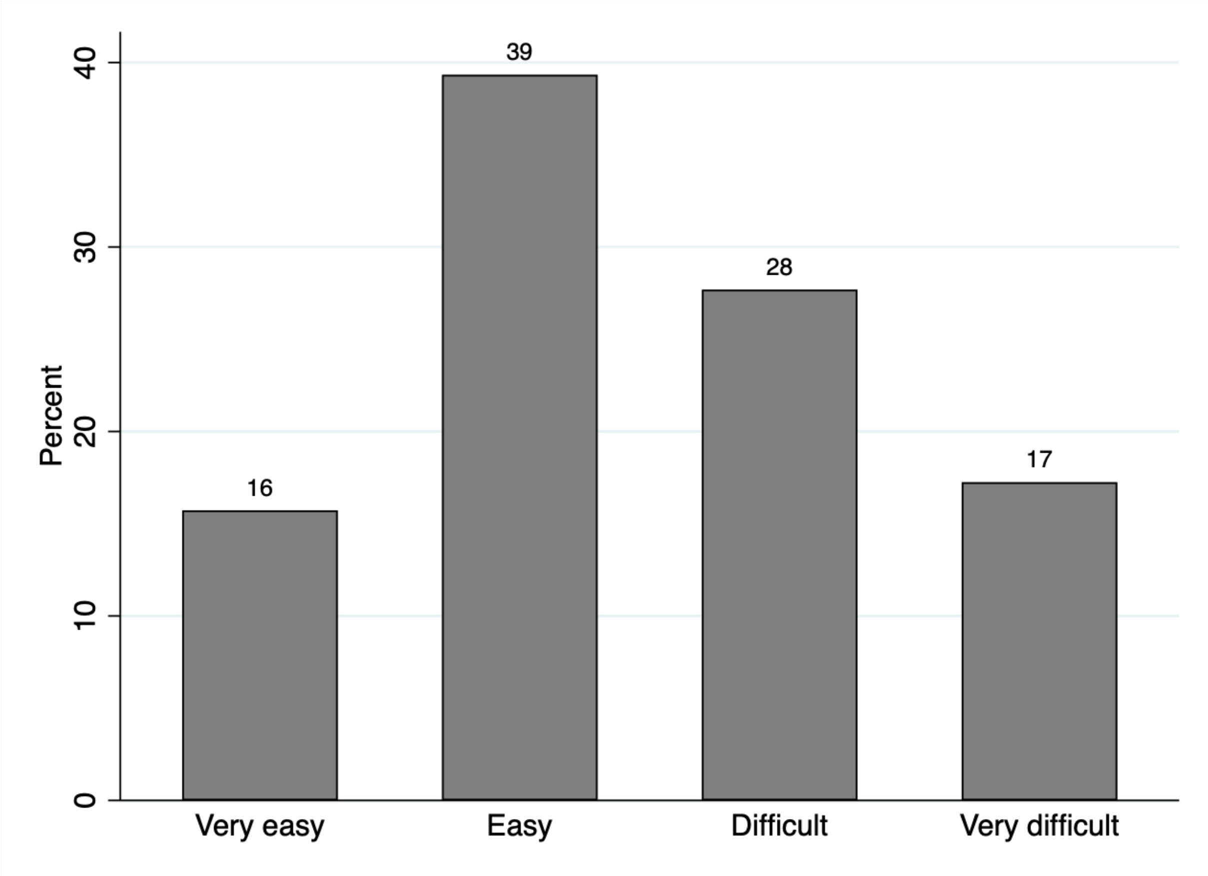

Figure A2: Africans' ease of accessing healthcare

Note: This figure presents responses to a question asking respondents to assess how easy it was for them to access healthcare. The horizontal axis indicates the different levels of ease, while the vertical axis represents the percentage of respondents corresponding to each level. The figure is based on survey data from Round 9 of the Afrobarometer survey, conducted across 39 African countries between 2021 and 2023.

Table A3: Replicating the results in Table 1 using the subsample of respondents who experienced at least one conflict incident within the 30 km radius

Dependent variables:	Contacted hospital			Poor healthcare index		
	(1) LPM	(2) LPM	(3) LPM	(4) OLS	(5) OLS	(6) OLS
Violent conflict$^{\sigma}$	-0.032***	-0.029***	-0.015***	0.216***	0.123***	0.071***
	(0.002)	(0.002)	(0.002)	(0.023)	(0.023)	(0.025)
Constant	0.573***	0.481***	0.414***	5.808***	4.227***	6.121***
	(0.002)	(0.01)	(0.018)	(0.022)	(0.094)	(0.174)
Control variables	No	Yes	Yes	No	Yes	Yes
Country Fixed effects	No	No	Yes	No	No	Yes
Observations	44463	44095	44095	25040	24865	24865
R-squared	0.005	0.015	0.083	0.003	0.065	0.174
AIC statistic	63434.83	62454.58	59387.7	133359	130825.2	127830.3
BIC statistic	63452.24	62506.75	59761.54	133375.3	130873.9	128179.5

Note: σ indicates that a variable is standardized. Violent conflict is measured using a radius of 30 km. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Models 1, 2, and 3 are estimated using linear probability model (LPM), while Models 4, 5, and 6 are estimated using ordinary least squares (OLS) regression. The dependent variable in Models 1 to 3, which is measured on a binary scale, indicates whether or not respondents had contact with a clinic or hospital in the past year. The dependent variable in Models 4 to 6 is an additive index ranging from 0 to 12, which measures respondent's assessment of the quality of healthcare they received when they visited a clinic or hospital. Control variables include poverty, educational level, and respondents' age and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted between 2021 and 2023 across 39 African countries.

Table A4: Replicating the results from Table 2 using the subsample of respondents who experienced at least one conflict incident within the 30 km radius

Dependent variables:	Respectful staff			Bribed staff		
	(1) Ologit	(2) Ologit	(3) Ologit	(4) Ologit	(5) Ologit	(6) Ologit
Violent conflict$^{\sigma}$	-0.057***	-0.02*	-0.019 (p=0.14)	0.167***	0.158***	0.041**
	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.017)
Intercept 1	-1.702***	-1.794***	-1.408***	1.338***	1.014***	0.666***
	(0.017)	(0.053)	(0.087)	(0.015)	(0.07)	(0.117)
Intercept 2	-0.566***	-0.645***	-0.228***	2.025***	1.708***	1.431***
	(0.013)	(0.051)	(0.087)	(0.02)	(0.07)	(0.117)
Intercept 3	0.589***	0.532***	1.008***	2.971***	2.658***	2.436***
	(0.013)	(0.051)	(0.087)	(0.029)	(0.073)	(0.12)
Control variables	No	Yes	Yes	No	Yes	Yes
Country Fixed effects	No	No	Yes	No	No	Yes
Observations	25316	25131	25131	25323	25140	25140
Pseudo R^2	0.00	0.009	0.031	0.004	0.013	0.086
Log pseudolikelihood	-33899.229	-33361.166	-32621.559	-18574.413	-18264.217	-16917.272
AIC statistic	67806.46	66738.33	65333.12	37156.83	36544.43	33924.54
BIC statistic	67839.02	66803.39	65699.05	37189.38	36609.49	34290.49

Note: σ indicates that a variable is standardized. Violent conflict is measured using a radius of 30 km. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10. All models are estimated using ordered logit (Ologit) regression. The dependent variable in Models 1 to 3, which is measured on a scale with four ordinal categories, captures respondents' assessment of the level of respect with which they were treated by hospital staff when they visited the hospital. The dependent variable in Models 4 to 6, which is also measured on a scale with four ordinal categories, captures the frequency with which respondents paid a bribe to hospital staff in order to receive the medical care they needed. Control variables include poverty, educational level, and respondents' age and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted between 2021 and 2023 across 39 African countries.

Table A5: Replicating the results from Table 1 while measuring violent conflict using a buffer of 20 km

Dependent variables:	Contacted hospital			Poor healthcare index		
	(1) LPM	(2) LPM	(3) LPM	(4) OLS	(5) OLS	(6) OLS
Violent conflict$^{\sigma}$	-0.034***	-0.031***	-0.015***	0.221***	0.118***	0.062**
	(0.002)	(0.002)	(0.002)	(0.023)	(0.022)	(0.024)
Constant	0.577***	0.486***	0.416***	5.8***	4.223***	6.11***
	(0.002)	(0.009)	(0.017)	(0.02)	(0.085)	(0.166)
Control variables	No	Yes	Yes	No	Yes	Yes
Country Fixed effects	No	No	Yes	No	No	Yes
Observations	53405	52927	52927	30396	30161	30161
R-squared	0.005	0.014	0.081	0.003	0.069	0.177
AIC statistic	75977.88	74801.5	71149.43	162071	158721.8	155088.8
BIC statistic	75995.66	74854.76	71540	162087.6	158771.7	155454.7

Note: σ indicates that a variable is standardized. Violent conflict is measured using a radius of 20 km. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Models 1, 2, and 3 are estimated using linear probability model (LPM), while Models 4, 5, and 6 are estimated using ordinary least squares (OLS) regression. The dependent variable in Models 1 to 3, which is measured on a binary scale, indicates whether or not respondents had contact with a clinic or hospital in the past year. The dependent variable in Models 4 to 6 is an additive index ranging from 0 to 12, which measures respondents' assessments of the quality of healthcare they received when they visited a clinic or hospital. Control variables include poverty, educational level, age, and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted between 2021 and 2023 across 39 African countries.

Table A6: Replicating the results from Table 1 while measuring violent conflict using a buffer of 10 km

Dependent variables:	Contacted hospital			Poor healthcare index		
	(1) LPM	(2) LPM	(3) LPM	(4) OLS	(5) OLS	(6) OLS
Violent conflict$^{\sigma}$	-0.029***	-0.026***	-0.012***	0.187***	0.095***	0.05**
	(0.002)	(0.002)	(0.002)	(0.022)	(0.021)	(0.022)
Constant	0.577***	0.488***	0.417***	5.796***	4.218***	6.106***
	(0.002)	(0.009)	(0.017)	(0.02)	(0.085)	(0.166)
Control variables	No	Yes	Yes	No	Yes	Yes
Country Fixed effects	No	No	Yes	No	No	Yes
Observations	53405	52927	52927	30396	30161	30161
R-squared	0.003	0.013	0.081	0.002	0.069	0.177
AIC statistic	76049.55	74866.25	71162.72	162090.6	158729.8	155090.6
BIC statistic	76067.32	74919.51	71553.3	162107.2	158779.7	155456.4

Note: σ indicates that a variable is standardized. Violent conflict is measured using a radius of 10 km. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Models 1, 2, and 3 are estimated using linear probability model (LPM), while Models 4, 5, and 6 are estimated using ordinary least squares (OLS) regression. The dependent variable in Models 1 to 3, which is measured on a binary scale, indicates whether or not respondents had contact with a clinic or hospital in the past year. The dependent variable in Models 4 to 6 is an additive index ranging from 0 to 12, which measures respondents' assessments of the quality of healthcare they received when they visited a clinic or hospital. Control variables include poverty, educational level, age, and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted between 2021 and 2023 across 39 African countries.

Table A7: Replicating the results from Table 2 while measuring violent conflict using a buffer of 20 km

Dependent variables:	Respectful staff			Bribed staff		
	(1) Ologit	(2) Ologit	(3) Ologit	(4) Ologit	(5) Ologit	(6) Ologit
Violent conflict$^{\sigma}$	-0.059***	-0.022**	-0.022*	0.169***	0.164***	0.054***
	(0.011)	(0.011)	(0.012)	(0.013)	(0.014)	(0.015)
Intercept 1	-1.705***	-1.809***	-1.413***	1.38***	0.999***	0.722***
	(0.016)	(0.048)	(0.083)	(0.014)	(0.063)	(0.112)
Intercept 2	-0.579***	-0.668***	-0.239***	2.062***	1.689***	1.48***
	(0.012)	(0.046)	(0.082)	(0.018)	(0.064)	(0.112)
Intercept 3	0.574***	0.506***	1.001***	3.008***	2.638***	2.482***
	(0.012)	(0.046)	(0.082)	(0.027)	(0.067)	(0.114)
Control variables	No	Yes	Yes	No	Yes	Yes
Country Fixed effects	No	No	Yes	No	No	Yes
Observations	30761	30509	30509	30784	30534	30534
Pseudo R^2	0.00	0.009	0.033	0.003	0.014	0.087
Log pseudolikelihood	-41113.608	-40430.177	-39453.488	-21931.667	-21525.734	-19929.709
AIC statistic	82235.22	80876.35	78998.98	43871.33	43067.47	39951.42
BIC statistic	82268.55	80942.96	79381.96	43904.67	43134.08	40334.44

Note: σ indicates that a variable is standardized. Violent conflict is measured using a radius of 20 km. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10. All models are estimated using ordered logit (Ologit) regression. The dependent variable in Models 1 to 3, which is measured on a scale with four ordinal categories, captures respondents' assessment of the level of respect with which they were treated by staff when they visited the facility. The dependent variable in Models 4 to 6, which is also measured on a scale with four ordinal categories, captures the frequency with which respondents paid a bribe to staff in order to receive the medical care they needed. Control variables include poverty, educational level, and respondents' age and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted between 2021 and 2023 across 39 African countries.

Table A8: Replicating the results from Table 2 while measuring violent conflict using a buffer of 10 km

Dependent variables:	Respectful staff			Bribed staff		
	(1) Ologit	(2) Ologit	(3) Ologit	(4) Ologit	(5) Ologit	(6) Ologit
Violent conflict$^{\sigma}$	-0.063***	-0.03***	-0.031***	0.144***	0.141***	0.043***
	(0.011)	(0.011)	(0.012)	(0.014)	(0.014)	(0.013)
Intercept 1	-1.706***	-1.807***	-1.416***	1.382***	1.007***	0.727***
	(0.016)	(0.048)	(0.083)	(0.014)	(0.063)	(0.112)
Intercept 2	-00.579***	-0.666***	-0.242***	2.062***	1.697***	1.484***
	(0.012)	(0.046)	(0.082)	(0.018)	(0.064)	(0.112)
Intercept 3	0.574***	0.508***	0.998***	3.008***	2.646***	2.486***
	(0.012)	(0.046)	(0.082)	(0.027)	(0.066)	(0.114)
Control variables	No	Yes	Yes	No	Yes	Yes
Country Fixed effects	No	No	Yes	No	No	Yes
Observations	30761	30509	30509	30784	30534	30534
Pseudo R^2	0.00	0.009	0.033	0.003	0.013	0.087
Log pseudolikelihood	-41110.725	-40428.498	-39451.89	-21950.358	-21541.867	-19931.096
AIC statistic	82229.45	80873	78995.78	43908.72	43099.73	39954.19
BIC statistic	82262.79	80939.6	79378.77	43942.06	43166.35	40337.22

Note: σ indicates that a variable is standardized. Violent conflict is measured using a radius of 10 km. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10. All models are estimated using ordered logit (Ologit) regression. The dependent variable in Models 1 to 3, which is measured on a scale with four ordinal categories, captures respondents' assessment of the level of respect with which they were treated by staff when they visited the facility. The dependent variable in Models 4 to 6, which is also measured on a scale with four ordinal categories, captures the frequency with which respondents paid a bribe to staff in order to receive the medical care they needed. Control variables include poverty, educational level, and respondents' age and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted between 2021 and 2023 across 39 African countries.

Table A9: List of 39 countries in the sample

Country	Frequency	Percent
Angola	1200	2.25
Benin	1200	2.25
Botswana	1200	2.25
Burkina Faso	1200	2.25
Cabo Verde	1199	2.24
Cameroon	1200	2.25
Congo-Brazzaville	1200	2.25
Côte d'Ivoire	1200	2.25
Eswatini	1200	2.25
Ethiopia	2400	4.49
Gabon	1200	2.25
Gambia	1200	2.25
Ghana	2369	4.43
Guinea	1200	2.25
Kenya	2400	4.49
Lesotho	1200	2.25
Liberia	1200	2.25
Madagascar	1200	2.25
Malawi	1200	2.25
Mali	1200	2.25
Mauritania	1200	2.25
Mauritius	1200	2.25
Morocco	1200	2.25
Mozambique	1120	2.10
Namibia	1200	2.25
Niger	1200	2.25
Nigeria	1600	2.99
São Tomé and Príncipe	1200	2.25
Senegal	1200	2.25
Seychelles	1176	2.20
Sierra Leone	1200	2.25
South Africa	1580	2.96
Sudan	1200	2.25
Tanzania	2400	4.49
Togo	1200	2.25
Tunisia	1200	2.25
Uganda	2400	4.49
Zambia	1200	2.25
Zimbabwe	1200	2.25
Total	**53,444**	**100.00**