A safe place to ask? Identity, privacy, and checking when LGBTQIA+ adults use AI for climate information in Nigeria's South-South

Ejiroghene Breadi Mitini (corresponding author)
Independent Researcher, Warri, Delta State, Nigeria
ejirobready@gmail.com , https://orcid.org/0009-0002-6099-5591

Edet Ekpenyong Akpaso
Outreach for Affirming Spaces, Inclusion and Sustainability (OASIS), Nigeria
edetakpaso@oasisinnigeria.org , https://orcid.org/0009-0000-4738-7781

Uka Uka Nwagbara
Outreach for Affirming Spaces, Inclusion and Sustainability (OASIS), Nigeria
uunwagbara@oasisinnigeria.org , https://orcid.org/0009-0006-8842-9646

Abstract:
In Nigeria's flood-prone South-South, lesbian, gay, bisexual, transgender, queer and intersex and asexual (LGBTQIA+) adults are more frequently relying on general-purpose artificial intelligence (AI) tools to decipher climate information. This study on 502 LGBTQIA+ AI users in Calabar, Uyo, Warri, and Yenagoa used the typologies of minority stress theory and Communication Privacy Management theory to explore the sources of their climate information, the motives for using AI, whether they verified information from AI, and who they would rely on for information. More than half of the information AI received was via WhatsApp (72.3%), and 42.8% cited no official agency. Almost all respondents in local language used English, Pidgin or a combination of both. Weaker reporting of increased safety reasons for using AI by transgender/intersex, disabled and displaced participants. There was no significant difference in OR for the relationship between privacy worry and checking while there was a significant OR for the relationship between digital skills and checking. Interestingly, without official sources, participants did not appear to be less likely to accept official messages; trust in AI was the strongest predictor of adherence to AI. Warning agencies should post verified multilingual messages via WhatsApp and community organisations should develop checking skills and not rely on privacy warnings.

Keywords: *Artificial intelligence; Climate communication; LGBTQIA+; Privacy; Flood warnings; Nigeria*

1. Introduction

From 2008 to 2024, Nigeria witnessed approximately 9.9 million disaster-induced movements, making it the leading country for displacement in Africa (Internal Displacement Monitoring Centre [IDMC], 2026). Bayelsa, Cross River and Delta were among the states vulnerable to coastal and tidal flood (Nigeria Hydrological Services Agency [NIHSA] 2025), and 729,310 persons were displaced during the 2024 floods (National Emergency Management Agency [NEMA] 2024). Residents are warned of these hazards primarily through radio, television and, increasingly, the use of WhatsApp, with the language of warning often being technical English (Ojo et al., 2025; Olajide, 2023).

General-purpose artificial intelligence (AI) like ChatGPT or Meta AI in WhatsApp has now started to intervene between these warnings and the recipients. This new go-between could have a special significance for lesbian, gay, bisexual, transgender, queer, intersex and asexual (LGBTQIA+) adults. Since the Same Sex Marriage (Prohibition) Act 2014, many have learnt to hide their identity from officials, neighbours and religious leaders (Schwartz et al., 2015; The Initiative for Equal Rights [TIERs], 2023). This pattern can be attributed to minority stress theory, which posits that individuals who anticipate rejection are scanning for threat and hiding their identity (Meyer, 2003; Frost & Meyer, 2023). Thus, an AI system that does not require face-to-face interaction can be a safe environment to pose a question.

But when it comes to safety from people, it's not the same as safety of data. According to Communication Privacy Management (CPM) theory, individuals regard information as their possession and establish guidelines on who can be granted access (Petronio, 2002; Petronio & Child, 2020). When a flood question is typed into Meta AI, the information is handed to a company that a Nigerian tribunal ruled in April 2025 had violated data protection laws impacting over 51 million users (Onyekachi, 2025). This study is thus bounded by three relationships. If people think they have to go to AI, they go to AI – this is what is expected to happen. Their decision to check what AI says might be influenced by privacy concern. Sources people typically trust can influence whose advice to follow when there is a discrepancy between AI and an official warning.

These relationships are unknown because of the presence of three gaps. The first is a gap in the population. Despite the fact that gender minority stress is unique (Hendricks & Testa, 2012) and disability presents its own challenges when accessing warnings (United Nations Office for Disaster Risk Reduction [UNDRR], 2023), disaster research on sexual and gender minorities typically groups them together (Dominey-Howes et al., 2014; Mortensen et al., 2025). Whether transgender, intersex, disabled or displaced LGBTQIA+ adults turn to AI for different reasons has not been tested.

The second is a thematic gap. In the privacy literature, there is the worry that worry doesn't change behaviour (Kokolakis, 2017; Hoffmann et al., 2016), and in the AI literature, it is found that many people do not check the answers of chatbots (Liao & Sundar, 2026). Almost all this evidence has been derived from samples from online in Europe, North America and East Asia. The extent to which privacy concerns would result in checking among those exposed who might be at legal risk has not been studied.

The third gap is a methodological one. While the research on warning has explored the sources from which warnings are received (Abenu, 2026; Ojo et al., 2025), it has rarely investigated how the source may influence decisions when there are competing sources.

1.3 Objectives and hypotheses

The study aims to examine how identity, privacy and information sources shape the way LGBTQIA+ adults in Calabar, Uyo, Warri and Yenagoa rely on AI for climate information. Its objectives are to (1) describe where the climate information people take to AI comes from, and whether they ask AI in a language other than the one they prefer; (2) compare transgender/intersex, disabled and displaced participants with others on using AI because asking a

person feels unsafe; (3) examine how privacy worry relates to checking AI's answers; and (4) examine what people would do when AI and an official warning disagree, and whether this depends on their usual sources.

Three hypotheses were tested. H1: transgender/intersex, disabled and displaced participants report stronger safety reasons for using AI than other participants. H2: greater worry about the privacy of what is typed into AI predicts more frequent checking. H3: participants whose climate information comes from no official agency are less likely to follow an official warning that conflicts with AI.

2 Literature review

2.1 Theoretical framework

According to minority stress theory, stigmatised individuals are said to experience two types of stress (Meyer, 2003). Outside events are called distal stressors, such as discrimination and violence. Proximal stressors: within the person (anticipation of rejection, concealment of one's identity, and assimilation of negative self-images). Both are supported by evidence from Nigeria. In a study in south-west Nigeria, gay men were over three times as likely as heterosexual men to report feeling depressed (16% compared to 4.9%) and a further 14% of the difference was explained by perceived stigma (Oginni et al., 2018). The minority stress scale has been found to have good test–retest reliability in Nigeria, but safety fears and concealment and hostile health workers were reported as the two main stresses in 20 interviews with Nigerian men (Makanjuola et al., 2018). However, these studies were conducted with cisgender men, who were recruited via organisations serving gay and bisexual men. They do not mention much about women, transgender or intersex people or about the mundane task of reading a flood warning.

Minority stress theory accounts for the fact that someone may not ask a person but the information they then provide to a machine remains unknown. CPM addresses this need (Petronio, 2002). It considers disclosure as transgression; once disclosed, the recipient is a co-owner, and there is "turbulence" when the recipient does something with it that wasn't anticipated by the owner (Petronio & Child, 2020). The two theories are of opposing forces. Minority stress is a predictor of flight from human judgement towards AI. CPM anticipates some wariness when it comes to AI as a new co-owner of private data. Both theories, however, were developed in Western contexts and Frost and Meyer (2023) cautions that stress processes are context-specific to law.

2.2 Stigma, intersecting disadvantage and safe interpreters

Other research on Australian floods and broader research on recovery systems connects the exclusion of sexual and gender minorities from relief to shelter, faith-based assistance and family-based registration (Gorman-Murray et al., 2017; King, 2022). However, much of this research is based on the idea that disadvantage is compounding: transgender and disabled/displaced people should have more obstacles to overcome than others. According to intersectionality theory, disadvantages can interact in less predictable ways (Crenshaw, 1989). Hendricks and Testa (2012) show that transgender people meet stressors, such as being misgendered on identity documents, that sexual minorities may not. There is a second layer of disability: only 11% of disabled people were aware of a national disaster plan and 84% had no personal plans

(UNDRR, 2023) across 6,342 responses from 132 countries. The potential for these layers to lead to increased motivations to avoid people has not been evaluated.

The evidence regarding Chatbots as ‘safe' listeners is encouraging yet sparse. While some chatbots did not address actual hazards like coming out to unsupportive parents, some U.S. LGBTQ+ users reported that they used chatbots as a place to practice painful conversations. Similarly, Nigerian users appreciated that AI could answer mental health related questions without exposing their identities and they approached it with a cautious stance to build trust (Nwagbara & Dennis, 2025). However, Ma et al. only interviewed 18 LGBTQ+ participants and neither study examined LGBTQIA+ subgroups.

2.3 Privacy worry and checking

The "privacy paradox" refers to individuals who express concern about privacy but behave as if they are not. The gap was deemed to be common but not universal, as found in the review of the evidence (Kokolakis, 2017). Now it is said that it is not irrationality, but resignation. The term "privacy cynicism" was coined by Hoffmann et al. (2016), referring to the notion that privacy protection is impossible to achieve, and Draper and Turow (2019) suggest that companies want people to feel that way. German survey findings reveal cynicism as a defence strategy to reconcile being included online and wanting privacy (Lutz et al., 2020) and further research has also shown that cynicism is not equally distributed across social groups (Hoffmann et al., 2024). None asks if there is a difference in how people handle the answers they get due to the concern for privacy.

Study of checking AI answers suggests skills/tendency to trust the AI over worry. A study conducted on 477 U.S. adults found that half of the respondents who were provided with the option to check facts did, and that fact-checking reduced trust in a chatbot that disseminated false health information (Liao & Sundar, 2026). The study included a survey of 319 knowledge workers that revealed that increased trust in generative AI was correlated with reduced critical thinking, but increased self-confidence was correlated with increased critical thinking (Lee et al., 2025). In six countries, many users indicated that they use the AI answers as a starting point, but verify them for health or politics (Simon et al., 2025). The conclusions vary with respect to the importance of trust, and the samples are from settings where there is little liability for exposure.

2.4 Sources, language and conflicting advice

Official warnings are a consistent predictor of protective action in warning research. Evacuation was the only factor found to have consistent effects in a meta-analysis of 49 studies on hurricanes, while most demographic factors had weak effects (Huang et al., 2016). Trust in authorities, however, can also be a substitute for one's own judgement (Wachinger et al., 2013) and in Nigeria trust is fragile. Some displaced LGBTQIA+ people felt that their identity made them ineligible for assistance (Nwagbara, 2026), while others in Akure and Kaduna received warnings that were of limited effectiveness (Abenu, 2026; Ojo et al., 2025). The focus groups conducted in six African countries showed that young people share unverified information for civic duty or for fun (Madrid-Morales et al., 2021), and a disaster communication review article highlighted that social media contains rumours, along with official information (Zhang et al., 2019). It would seem logical to suggest that if the

only way to obtain information is through informal means that official warnings are given less consideration.

There is another filter – language. Large language models have been found to work much worse in African languages than English (Adelani et al., 2025) and their ability to translate Nigerian Pidgin is poor (Nwafor & Nguyen, 2025). In Kenya, climate services were not equitably distributed by language and gender (Bullock & Katothya, 2022) and accessible communication requires dialogue, not just translation (Mabon, 2020). Studies, however, that rank barriers across entire samples may obscure a minority for which language is of great importance namely those of the Efik, Ibibio, Ijaw, Urhobo and Itsekiri speakers for whom AI is the worst.

3. Methodology

3.1 Design and sample

This study analyses a cross-sectional survey of 502 LGBTQIA+ adults in Calabar (n = 128), Uyo (n = 114), Warri (n = 137) and Yenagoa (n = 123). All of the following analyses were conducted after the hypotheses listed above were formulated.

As there was no list of LGBTQIA+ adults and an open ad campaign would leave these adults vulnerable to homophobia and transphobia under the 2014 Act, recruitment started with 6-8 trusted community organisations city. These participants then distributed three coded coupons to other participants (Heckathorn, 1997). However, results pertain to this sample only, as its statistical assumptions are often not met (Johnston & Sabin, 2010). Those eligible were 18+, self-described as LGBTQIA+, lived in their city for 12 months or longer, and used AI for climate information in the past year.

3.2 Measures

The information sources were based on item B10 where several answers were possible. Sources were categorized into official agencies (Nigerian Meteorological Agency [NiMet], NIHSA or a state emergency agency), radio or television, social media (WhatsApp, Facebook, X/Twitter or TikTok) and people (friends or family, community leaders and religious places). If the participant for H3 did not identify any official agency, they were coded "no official source". A more stringent check coded those who did not mention any official agency, nor radio or television. Language mismatch had to do with the fact that the preferred language for important information (F9) was not the language used to ask AI (B9).

The groups were divided in accordance with the coding of the questionnaire. Participants were coded as transgender/intersex = 1 if they responded F4 or F5, disability = 1 if they responded F6, and displacement = 1 if they responded F7 (a yes answer to any of the displacement questions). Unsure" and prefer not to answer" were coded as missing, and 414 had a transgender/intersex response and 448 provided a disability answer, since putting such pressure on individuals to reveal a response tends to produce inaccurate answers (Tourangeau & Yan, 2007).

H1 intended to score between C7 (I did not feel safe asking a person) and E5 (I feel safer asking AI than a person because of my identity). The correlation between the two items was hardly significant (Spearman's $\rho = .09$; Cronbach's $\alpha = .17$) and they were therefore also analysed separately. H2 applied both E9 (privacy worry) and E8 (checking AI against another source)

on a scale of 5. H3 asked about E10 (0 = AI, 1 = follow official warning, or unsure = asking someone else). The control variables were age group, education, city, digital skills (F1-F13; α = .57) and trust in AI (E1-E7, omitting E5 to avoid overlap with H1; α = .34). These controls must be interpreted with caution as low reliability weakens the associations, and null results are more likely (Schmitt, 1996).

3.3 Analysis

Percentages and chi-square tests were used for Objective 1. H1 was tested with Mann–Whitney tests and effect size computed as r (Fritz et al., 2012) and Holm adjustment across tests (Holm, 1979) and a regression of the safety average on all three group indicators and controls. H2 employed ordinal logistic regression suited to an answer on an ordered scale, and reported odds ratios (OR). H3 used chi-square tests and binary logistic regression. 28 participants were excluded from regressions because they failed to report on age or education, resulting in 474. Python (SciPy 1.17) was used for analyses.

3.4 Ethics

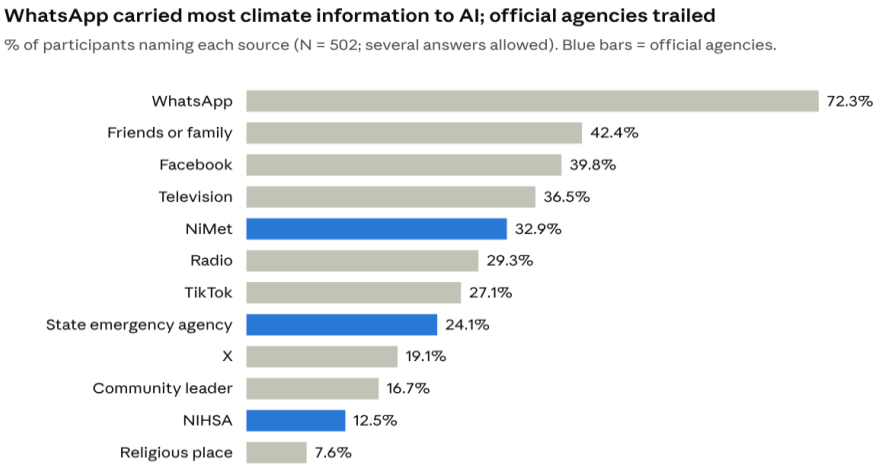
Prior to fieldwork, ethical clearance was received from an institutional health research ethics committee (not disclosed for review). Names, telephone numbers, addresses were not gathered, the coupons contained only codes, and results are given only by city/ group. All participants were given a partner organisation's helpline for verified flood information.

4. Results

4.1 Where information came from, and in what language (objective 1)

Most climate information that participants took to AI came through WhatsApp (72.3%), and 89.4% named at least one social media platform (figure 1). Participants named a median of four sources. Just over half (57.2%) named an official agency, most often NiMet (32.9%); NIHSA, which issues the Annual Flood Outlook, was named by 12.5%. The share naming any official agency ranged from 51.8% in Uyo to 64.2% in Yenagoa, a difference that was not statistically significant, $\chi^2(3, N = 502) = 5.49$, $p = .139$. In all, 215 participants (42.8%) named no official agency, and 101 (20.1%) named neither an official agency nor radio or television.

Figure 1. *Sources of the climate information participants took to AI*



Source: survey item B10, N = 502

Language did not match for many participants. Of the 157 (31.3%) who preferred Efik, Ibibio, Ijaw, Urhobo or Itsekiri for important information, 154

asked AI in English (43.9%), a mix of languages (39.5%) or Pidgin (14.6%). Of the 151 who preferred Pidgin, only 49 (32.5%) asked AI in Pidgin. Local-language speakers were more likely than others to say they consulted AI because information was not in a language they understood well (C5: 24.8% against 16.8%; Mann–Whitney p = .025, r = .10).

4.2 Safety reasons by group (objective 2, H1)

The safety average did not differ between transgender/intersex, disabled or displaced participants and others (table 2). All differences were small (r = −.04 to .05) and none approached significance after Holm adjustment. Tests on C7 and E5 separately gave the same picture (all adjusted p ≥ .575). Transgender/intersex and disabled participants agreed slightly more often that asking a person felt unsafe, whereas displaced participants agreed less often (33.3% against 41.6%). Entering all three groups together with controls explained 3% of the variance, and the model was not significant, F(9, 340) = 1.24, p = .270. Only older age (B = 0.09, p = .036) and living in Warri (B = −0.27, p = .031) related to the safety average. $H0_1$ was retained.

Table 2. Safety reasons for using AI, by group.

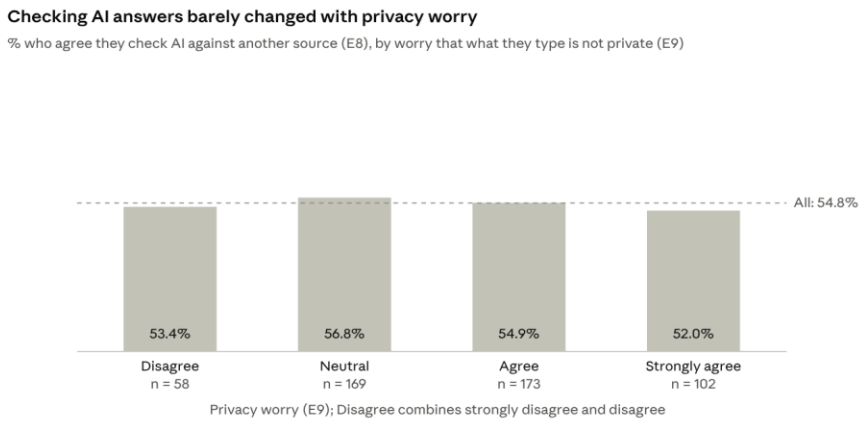
Group (yes / no)	Safety mean, yes / no	C7 agree %, yes / no	E5 agree %, yes / no	z	r	Holm p
Transgender/ intersex (87 / 327)	3.24 / 3.21	46.0 / 38.2	39.1 / 43.7	0.49	.02	.935
Disabled (69 / 379)	3.32 / 3.20	44.9 / 38.3	47.8 / 43.8	0.96	.05	.935
Displaced (129 / 373)	3.14 / 3.22	33.3 / 41.6	42.6 / 42.4	−1.00	−.04	.935

Note. Safety mean is the average of C7 and E5 (1–5). Agree = agree or strongly agree.

4.3 Privacy worry and checking (objective 3, H2)

Privacy worry was common (54.8% agreed), and so was checking (54.8%), but the two were unrelated, ρ = −.04, p = .382. Among participants worried about privacy, 53.8% checked AI against another source, compared with 55.9% of those not worried. With controls, privacy worry did not predict checking (OR = 0.94, p = .464), so $H0_2$ was retained (table 3). Digital skills were the strongest predictor: each one-point rise more than doubled the odds of checking more often. Trust in AI also went with more checking, not less.

Figure 2. *Checking AI answers by level of privacy worry*

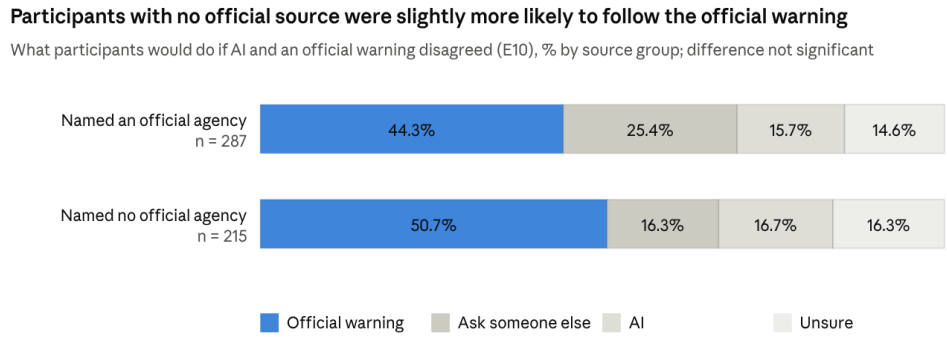


Source: survey items E8 and E9, N = 502

4.4 Conflicting advice (objective 4, H3)

Asked what they would do if AI and an official warning disagreed, 47.0% would follow the official warning, 21.5% would ask someone else, 16.1% would follow AI and 15.3% were unsure. Contrary to H3, participants who named no official agency were slightly *more* likely to follow the official warning (50.7%) than those who did (44.3%), $\chi^2(1, N = 502) = 1.80$, $p = .180$, Cramér's V = .06. Those who named an official agency more often said they would ask someone else (25.4% against 16.3%). The stricter coding gave the same direction (54.5% against 45.1%, $p = .117$). With controls, the odds ratio was 1.44 ($p = .058$), again opposite to the prediction, so $H0_3$ was retained. Trust in AI was the only clear predictor: higher trust halved the odds of following the official warning and, in a separate model, raised the odds of following AI (OR = 2.53, 95% CI [1.46, 4.36], $p = .001$). No subgroup differed in its answers (all $p \geq .133$).

Figure 3. *Response to conflicting AI and official advice, by whether participants named an official agency*



Source: survey items B10 and E10, N = 502; $\chi^2(1) = 1.80$, $p = .180$

Table 3. Predictors of checking AI (H2) and following the official warning (H3), n = 474.

Predictor	H2: checking, OR [95% CI]	p	H3: follow official, OR [95% CI]	p
Privacy worry (E9)	0.94 [0.79, 1.12]	.464	—	—

Predictor	H2: checking, OR [95% CI]	p	H3: follow official, OR [95% CI]	p
No official source	—	—	1.44 [0.99, 2.10]	.058
Digital skills	2.37 [1.76, 3.19]	< .001	0.84 [0.62, 1.15]	.283
Trust in AI	1.54 [1.08, 2.20]	.018	0.52 [0.35, 0.78]	.001
Age group	0.98 [0.83, 1.17]	.855	0.91 [0.76, 1.09]	.313
Education	1.05 [0.89, 1.24]	.566	1.11 [0.92, 1.33]	.285

Note. H2: ordinal logistic regression. H3: binary logistic regression. Both models control for city; no city effect was significant.

5. Discussion

As demonstrated in the first objective, the agencies responsible for flood warnings are only able to reach these AI users at second hand. Nearly three in four participants shared the information on WhatsApp, while about one in eight did on NIHSA, a publisher of the Annual Flood Outlook. This is consistent with evidence from Africa that messaging apps are now disseminating a lot of public information (Madrid-Morales et al., 2021) and with a review of disaster communication (Zhang et al., 2019). This is not as well received by Nigerian warning studies that continue to regard radio, TV and outlook as the principal media (Ojo et al., 2025; Olajide, 2023). This means that AI is frequently called upon to interpret a forwarded message, not the agency's.

Language indicates an obvious, though hidden cost. Almost all local language speakers posed questions to AI using English, Pidgin or a combination of both and reported that a language issue was a reason for seeking AI help. This indicates that language can be of critical importance to a minority even if it is not of much significance overall the sample as a whole. A possible interpretation of this is that the people "translate" themselves for the machine, making themselves comprehensible to it. This aligns with a study showing that models struggle with African languages and Pidgin (Adelani et al., 2025; Nwafor & Nguyen, 2025); and with the assertion of Mabon (2020) that access requires dialogue, not just translation. However, item B9 indicates usual practice, not ability and this reading should be tested.

The second objective was the most novel in comparison to the literature. There were no significant differences for stronger safety reasons for using AI reported by any transgender/intersex and disabled and displaced participants. This counteracts the idea, prevalent within the disaster studies field, that disadvantage is cumulative (Dominey-Howes et al., 2014; Gorman-Murray et al., 2017), and the expectation that the minority stress of being female adds additional stresses (Hendricks & Testa, 2012). It's impossible that the sample size was to blame, since the results seen in the study were much less than the subgroups would have been able to see. The more plausible explanation is in context. The 2014 Act could create such a uniform and extreme level of alertness for exposure that most LGBTQIA+ adults are at a high level of caution and few gradients exist between subgroups. The study's results point to the importance of considering the legal climate when examining minority stress processes: Frost and Meyer (2023) report that minority stress processes can vary depending on the legal climate, and that shared threat may obscure differences seen in more tolerant climates.

Much like the questions of asking a man or woman, displaced participants were less likely to report that this was unsafe, if at all. The difference was not significant, and can only raise a query. One option is that it takes away the option: it is a no choice situation where people in camps or in relief queues have to deal with officials and strangers regardless of whether they feel safe or not. Such a reading aligns with the experiences of queer people of colour who have been forced to seek services in systems that they do not trust (King, 2022; Nwagbara, 2026), and it suggests that avoidance is a luxury afforded to people who have not yet had to use services.

But the weak connection between C7 and E5 is not just a measurement issue, it's a discovery as well. The feeling of insecurity to ask a person, and the feeling of security to ask AI were not correlated. Minority stress theory explains the first which is a push away from people who are expected to reject them (Meyer, 2003). Not much can be said about the latter, a pull towards a machine. Indeed, according to Ma et al. (2024), users of LGBTQ+ chatbots appreciated the potential to rehearse and ask freely, which was a positive aspect of using the chatbots. The current information indicates that "safety" may contain two motives, that latter should be distinguished in future measures.

The third objective revealed that there was no relationship between privacy worry and privacy checking. This reflects the privacy paradox (Kokolakis, 2017), and accounts of privacy cynicism (Hoffmann et al., 2016; Draper & Turow, 2019) but builds upon these. Those studies demonstrate that worry is not always successful in altering what individuals reveal, and here worry was not successful in altering how individuals treated what they received. CPM's privacy rules apply to what goes across the boundary in the outward direction (Petronio & Child, 2020). Checking an answer is a judgement of accuracy, and this may be based on entirely different reasoning. The fear and anxiety that came with the 2025 Meta ruling (Onyekachi, 2025), therefore, may not have any tangible resolution.

What did predict checking was skill. Participants who were more digitally skilled tended to check more, and as Liao and Sundar (2026) demonstrated, verification is reliant on having a way to verify, while Lee et al. (2025) revealed that self-confidence contributes to critical thinking. But trust was accompanied by increased, not decreased, checking, both in opposition to Lee et al. (2025) and to the over-reliance theory of Lee and See (2004). One of the reasons is probably what the word “trust” meant there. The trust scale included accuracy and availability, as well as not judging the user, which corroborates the study conducted by Nwagbara and Dennis (2025) that anonymity is important to users in Nigeria. It may just be that the people who are trusting are the more engaged and heavier users who also refer to additional sources and use AI tools as a starting point, as Simon et al. (2025) put it. This explanation is provisional as the reliability of the trust scale was low ($\alpha = .34$).

The result of the fourth objective was contrary to the hypothesis. The willingness to follow an official warning had lower scores for those who knew no official agency and higher scores for those who named no official agency. One possible explanation is that familiarity breeds discernment. However, those who receive messages directly from NiMet or the state agency may also know their boundaries: late radio warnings and lack of local detail (Abenu, 2026; Ojo et al., 2025; Nwagbara, 2026), and therefore place their bets accordingly. The official warning may be an abstract authority for those who do not have direct

contact. In this context, "ask someone else" may be related to risk appraisal, rather than distrust, as noted by Wachinger et al. (2013) about the loss of personal judgement in favor of relying on authorities.

It was trust in AI, not in the information source, which changed choices towards AI. Trust reduced the chances of taking the official warning by 50%, and thus it seems that trust is not a function of the channels people use but an attitude. This is important because experts' tests reveal that AI is less effective in African context settings (Atkins et al., 2024; Moayeri et al., 2024). Trust, based on non-judgement, can thus cause a minority to accept advice that is locally incorrect and is what Lee and See (2004) call 'trusting beyond ability.

These readings are based on the single items or weak scales of self-reported, cross-sectional responses from AI users. The conflict question was also hypothetical but, as found by Huang et al. (2016), responses to hypothetical and actual questions were comparable for 10 of 17 evacuation factors. The results consequently establish associations, not causes.

6. Conclusions

This study explored the role of identity, privacy and information sources in the experiences of LGBTQIA+ adults in using AI for climate information. Warning agencies did not reach people with information, with WhatsApp being the main way information reached AI, and local-language speakers typically switched language to use AI. There was no greater sense of safety among transgender/intersex and disabled and displaced participants as compared to others when it came to using AI. It was not the privacy concern that made people check more – it was the digital skills. As expected, those who did not have official sources were not less likely to change their behavior in response to official messages, but instead it was trust in AI, not source, that drove decisions towards AI.

The study is a contribution in three aspects. To our knowledge, it is the first comparison of the use of AI by subgroups of Nigerian LGBTQIA+ adults, and it indicates that in a criminalising context, the intersectional differences that one would anticipate might be leveled. It reveals that the privacy paradox is not limited to what is divulged, but also to how privacy is evaluated – a dimension that CPM had not taken into account. It also proposes that "safety" in the use of AI involves moving away from people and moving toward machines, which minority stress theory only partially accounts for.

6.1 Recommendations

The immediate and least expensive action that can be taken is for NIHSA, NiMet and state emergency management agencies to disseminate concise and verified warnings via official WhatsApp channels in English, Pidgin and in Efik, Ibibio, Ijaw, Urhobo and Itsekiri languages. As most information already goes through WhatsApp, this would place the original message, instead of a forwarded version, in front of both users and the AI tools that they consult. Each should identify the affected communities and action to be taken.

LGBTQIA+ and disability and displacement organisations are a second priority. Skills – not worry – predicted checking is likely to do more than privacy warnings alone, with short peer-led sessions on comparing AI answers with official warnings in the balance. The examples of the coupon networks used in this study indicate that such networks can be effective in reaching beyond members and can be done at a low cost.

Thirdly, the Nigeria Data Protection Commission and AI vendors in Nigeria must, in local languages, provide clarity on how to handle locally typed questions into tools like Meta AI, in line with the Nigeria Data Protection Act 2023. This is not necessarily enough to alter behaviour, and is most useful for informed choice. Lastly, emergency agencies and researchers should document, with the consent of the person and proper precautions, if they are a person with a disability, displaced, transgender or intersex and their preferred language. This would provide an indication of the actual number of each group being reached with warnings, instead of leaving the needs to assumption.

6.2 Limitations and Future directions

The sample was only of people who already use AI, and was drawn from organisations and peer referral, meaning the results are not descriptive of people who do not use AI, or LGBTQIA+ people more broadly. Some of the most privacy-obsessed users may have been weeding out AI altogether and, in turn, not showing up in the study. The measures were weak (often single items, hypothetical conflict), and self-reported.

Future studies may involve a comparison of users and non-users to investigate if a lack of privacy is deterring users from using AI. It can also be used to substitute the single items that were used which have been subjected to testing in Nigeria such as the adapted minority stress scale (Ogunbajo et al., 2020) and also separate the push and pull factors of "safety". Participant consent was possible to log their actual checking over a rainy season, and experiments could be made to compare the interpretation of official and forwarded warnings in Pidgin and local languages by AI. Interviews with displaced participants would help explain if there is an option of avoiding people when in crisis.

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