
Research Report – Brief

Public Conversation on the 2026 East Nusa Tenggara Earthquake

An analysis of social media conversation
across 657 Instagram comments in the
first week after the earthquake

About this report

This report was produced by Impact Cannot Wait as an analysis of social media conversation about a disaster event. All figures come from public comments on publicly accessible Instagram posts, not from a survey. They must therefore not be read as representing the views of the population as a whole.

The dataset consists of 657 comments coded from 119 posts, collected on 22 August 2026. Supporting files, including the codebook, raw data, coded data, analysis scripts, and chart files, are available from the researchers so that every figure can be traced back to its source.

About Impact Cannot Wait:

Impact Cannot Wait is an independent initiative developing technology for research, policy, and social impact. We combine technology, data, and evidence to help governments, development partners, and civil society organisations make better decisions. Our focus spans AI and data, policy technology, digital public services, and technology for research and evaluation.

Evidence. Technology. Impact.

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Executive Summary

- 1. To examine what was being said on social media about the earthquake in East Nusa Tenggara,** 657 public comments were analysed across 119 Instagram posts from 76 different accounts during the first seven days after the M7.7 earthquake in East Nusa Tenggara, 15–22 August 2026, using thematic coding, non-organic content filtering, and regression analysis
- 2. The conversation was not dominated by anger or negative tone.** Negative comments account for 39.7 per cent, while positive and mixed comments combined reach 53.2 per cent.
- 3. What was discussed most concerns citizens, not government.** The citizen solidarity frame accounts for 19.0 per cent and conditions on the ground for 18.0 per cent, higher than any other frame.
- 4. What is written most is generally what is endorsed most, that is, what receives the most likes even there is a huge gap.** Criticism accounts for 24.2 per cent of comments but absorbs 62.3 per cent of likes, while requests for help account for 4.7 per cent of comments and only 0.5 per cent of likes. This does not change after regression with control variables.
- 5. Judgement of actors is split by role.** Volunteers receive 20 positive judgements against 0 negative and the armed forces (TNI) 27 positive against 2 negatives, while central government receives 23 positives against 170 negative and the national parliament (DPR) 1 positive against 14 negatives.
- 6. Where the conversation takes place is related to its content.** In the comment sections of citizen and local media accounts, the odds of a comment being criticism are about 0.25 times, and the odds of the solidarity frame about 2.7 times, those of other accounts.
- 7. There is no shift from grief towards judgement of performance.** The coefficient for days since the main earthquake is not significant; the composition of conversation in the first week is relatively stable and critical posts continue to rise.

Main implication. Social media monitoring during a disaster needs to separate comment function, not only tone. Requests for help, for example, receive the least endorsement and will be missed if monitoring follows only the popularity of posts and comments and the algorithm of the social media platform itself.

1. Introduction

On Saturday, 15 August 2026 at 05.58 WITA, an M7.7 earthquake struck off the northern coast of Flores Island, East Nusa Tenggara. BMKG, Indonesia's meteorological agency, attributed it to the Flores back-arc thrust (a fault type that pushes one section of the earth's crust up over another). It is recorded as the strongest earthquake in Flores since 1992. As of 21 August 2026, the national disaster agency BNPB recorded 78 deaths, 95,831 people displaced, and 38,898 houses damaged. Over the same period, more than 4,258 aftershocks were recorded.

This study does not measure the impact of the earthquake directly. Its focus is how the earthquake was talked about in digital space during the first week. There are three main questions: what was discussed most, how people discussed it, and which views attracted the most endorsement from readers.

The third question matters because social media is increasingly used to seek

information during disasters. If the views that attract the most likes (hereafter, endorsement) differ from what is discussed most often, monitoring that tracks only popularity can give a misleading picture of needs on the ground.

The study rests on three premises. First, social media comments are treated as public conversation, not as a sample of population opinion (a dataset that represents the population). Second, the number of likes is read as a signal of reader endorsement, not as evidence that the content of a comment is true. Third, not all comments come from ordinary members of the public. Screening for non-organic content (content suspected of being created or spread in a coordinated way) is therefore an essential part of the method.

2. Method

Collection and relevance screening

Eight earthquake-related hashtags were searched, yielding 862 initial posts. A post entered the sample if its caption contained

both a disaster-related term and a place name in East Nusa Tenggara or Flores, and was published on or after the date of the main earthquake. Posts were then ranked by number of comments. Because that approach tends to draw in busy and more political posts, a further 20 posts focused more closely on conditions on the ground were added. The eight hashtags were #gempanttt, #prayforntt, #gempaflor, #gempamanggarai, #floresbangkit, #gempaflor2026, #nttbangkit, and #gempanttt2026.

Screening of non-organic content

Comments were screened in two stages. The first stage removed duplicate comments, emoji-only comments, comments of fewer than two words, and comments that only tagged an account. The second stage removed three kinds of content not treated as public conversation: online gambling promotion, coordinated comment campaigns, and talking-point content (messages or sentence patterns repeated to support a particular party or institution). Campaign detection scores were mapped against manual reading to set the threshold used.

Coding framework

Every comment that passed screening was coded (assigned categories systematically) on three dimensions: tone, discourse frame (how the comment sees or explains an issue), and communicative function (what the comment is trying to do, for example to criticise or to inform). The researchers also recorded which actors were named, whether the judgement of them was positive or negative, the dominant emotion, and the factors seen as worsening or improving the situation. Each row stores the verbatim quotation and a one-sentence analytical note separately. This allows the reader to distinguish what the commenter said from what the researcher concluded.

Regression specification

Regression analysis (a statistical method for examining relationships between several factors) was used to check whether the patterns visible in the data persist once other factors are taken into account. The model specification is:

$$Y = F + N + Z + e$$

Y: Dependent variable: number of likes on the comment (Model 1) or the comment type being tested (Models 2 and 3).

F: Communicative function (what the comment is trying to do, for example to criticise, to inform, or to request help); emotional reaction is used as the reference category.

N: Comment tone (whether the comment is positive, negative, mixed, or neutral); neutral tone is used as the reference category.

Z: Control variables (other factors taken into account): log number of comments on the post, how long the comment has been visible, days since the main earthquake, and the type of posting account.

E: Standard error (the portion of variation the model cannot explain).

Model 1 uses negative binomial regression (a method for count data, particularly where counts are highly uneven) because the number of likes is heavily skewed and overdispersed (the variation in the data is greater than the model would normally assume). Models 2 and 3 use logit regression (a method for outcomes with only two possible values) because their outcome variables are binary (for example yes/no). Standard errors are clustered at post level because comments sit within the same post and cannot be treated as fully independent. The sample is purposive (selected on defined criteria), so the regression results show associations within the data analysed, not evidence of cause and effect.

3. Findings

3.1 Composition of the conversation: solidarity and descriptions of conditions stand out more than judgements of government

This section answers the first two questions: what was discussed and how people discussed it. Four measures are presented in turn: discourse frame, tone, comment function, and emotion.

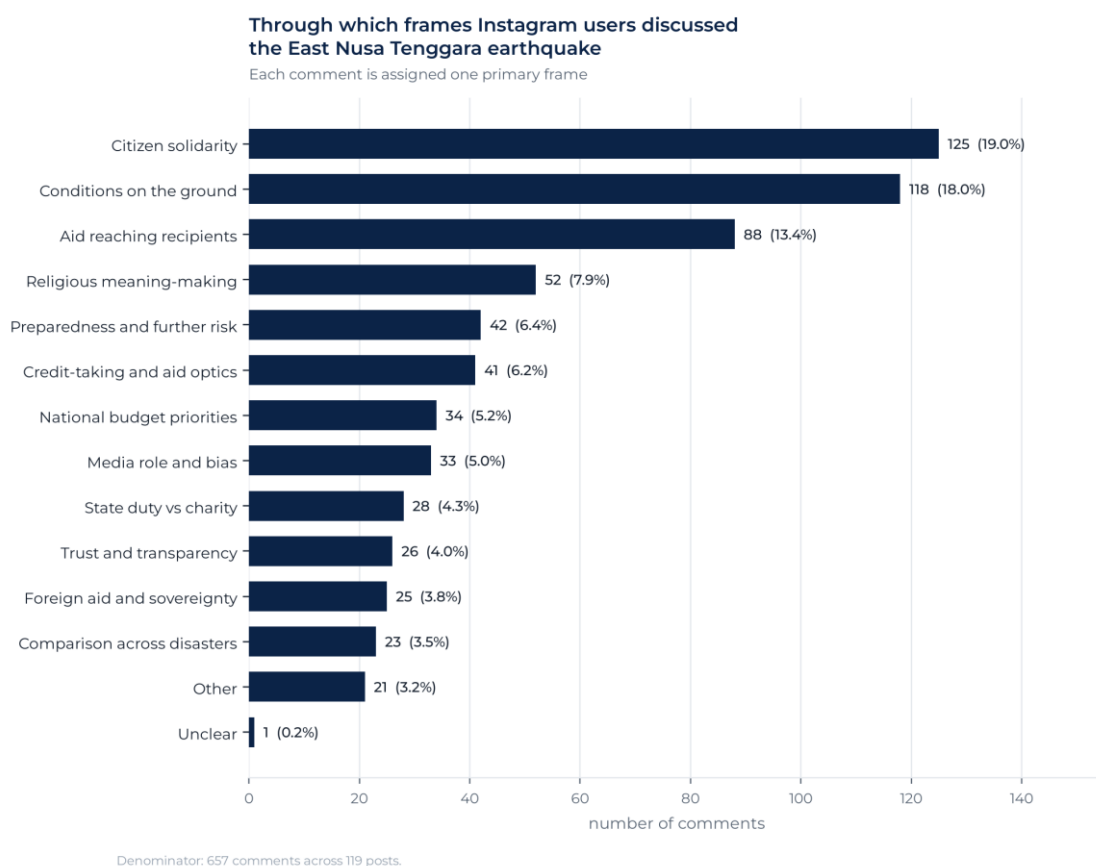


Figure 1. Discourse frames used by the comments.

The most common frame is citizen solidarity (125 comments, 19.0 per cent), followed by conditions on the ground (118 comments, 18.0 per cent) and aid reaching recipients (88 comments, 13.4 per cent). If the frames concerned with governance (how government and institutions manage public affairs) are combined — credit-taking for aid, budget priorities, state duty, and trust — they total 129 comments. That is still fewer than the combined comments on citizen solidarity and conditions on the ground. In the first week, therefore, the conversation contained more solidarity and description of conditions than judgement of government.

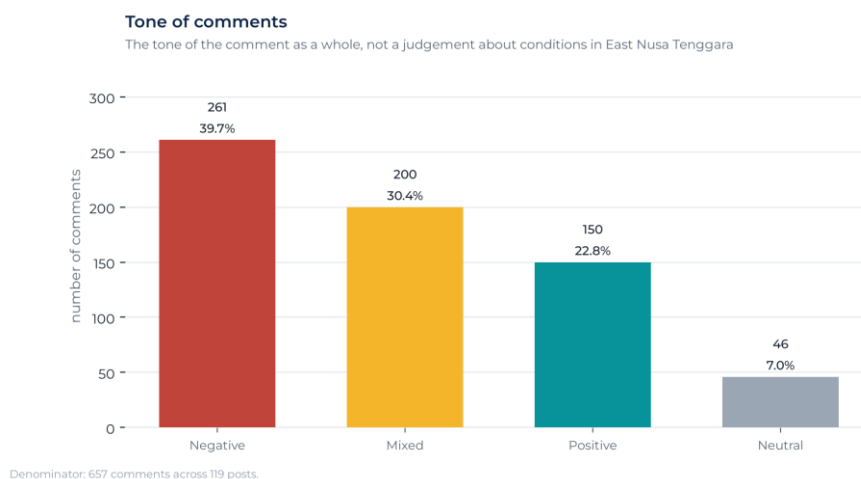


Figure 2. Distribution of comment tone.

Negative comments are the largest single group at 39.7 per cent, but they do not reach half of all comments. Positive comments account for 22.8 per cent and mixed comments for 30.4 per cent, together reaching 53.2 per cent. Conversation about the disaster therefore cannot be described as consisting only of anger. Mixed comments typically combine appreciation with a caveat, or criticism accompanied by prayer and hope.

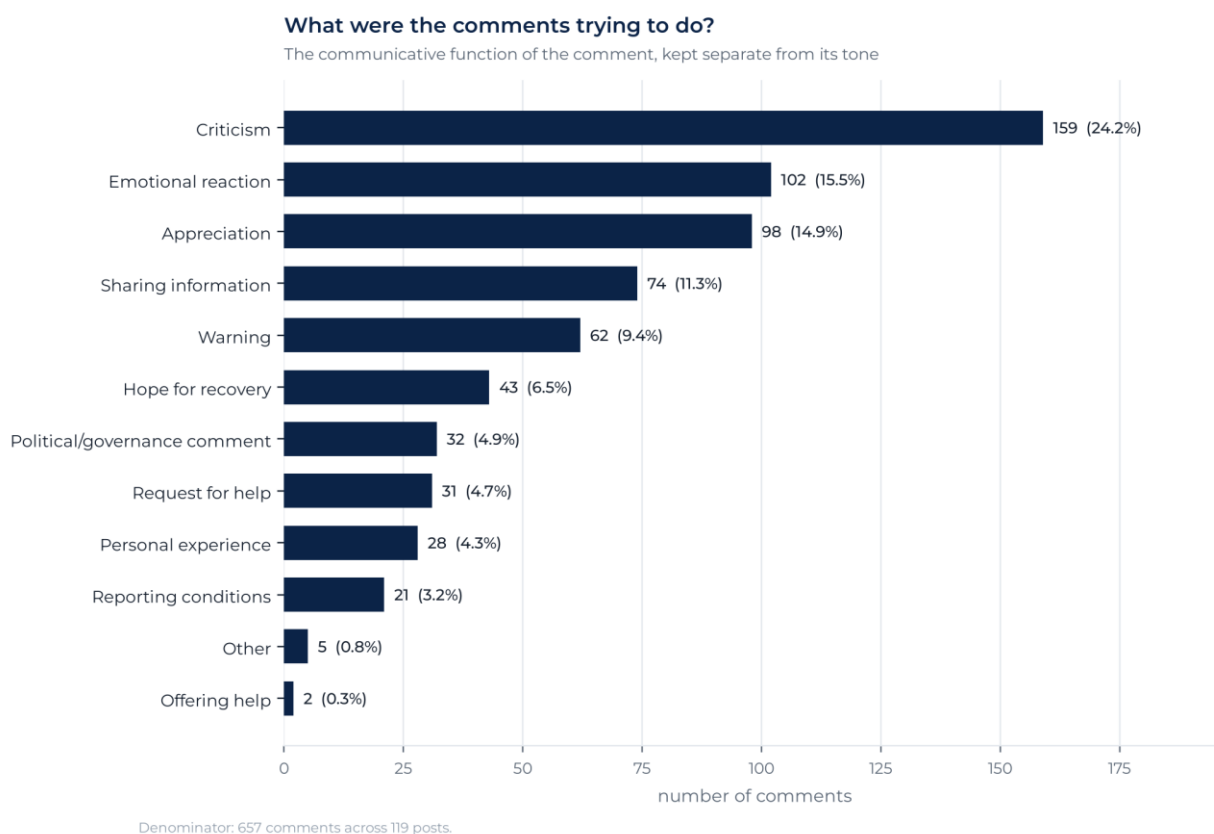


Figure 3. What the comments were trying to do.

The most common comment function is criticism (159 comments, 24.2 per cent), followed by emotional reaction (102 comments) and appreciation (98 comments). Function must be distinguished from tone because the two do not always align. A negative comment, for instance, may be a criticism, a warning, or a request for help. Each calls for a different response. Requests for help, which most clearly call for direct action, appear in only 4.7 per cent of comments.

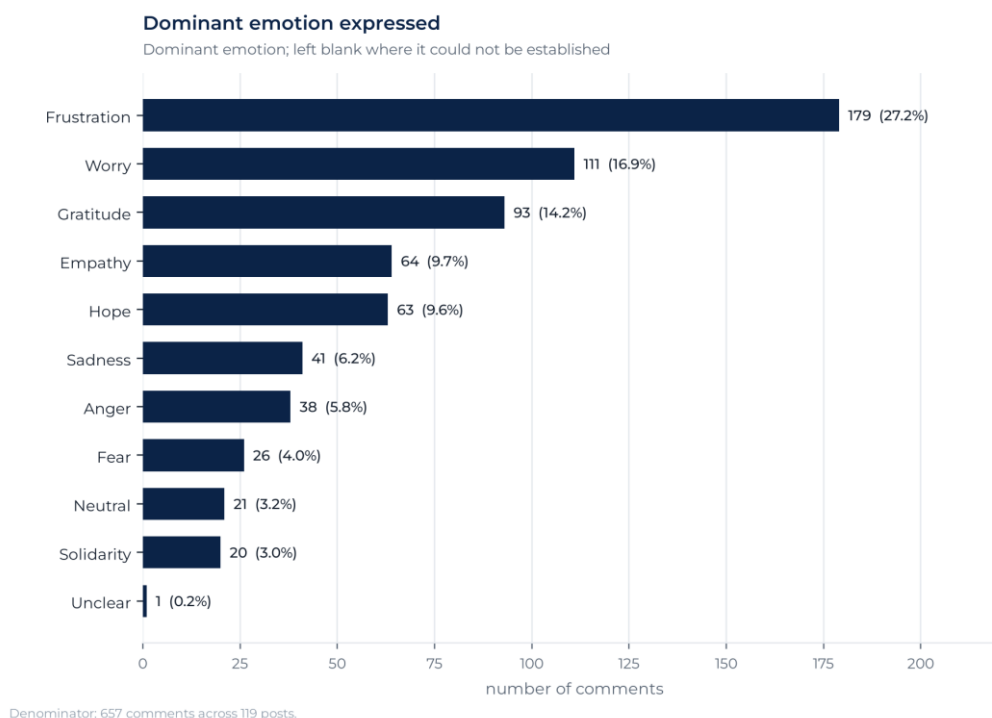


Figure 4. Dominant emotion expressed.

The most frequent emotion is frustration (179 comments, 27.2 per cent), followed by worry (111) and gratitude (93). This complements the findings on tone. Emotions such as empathy, gratitude, solidarity, and hope appear more often than anger. Anger appears mainly in comments about governance (how government or institutions handle public affairs), not in comments about conditions on the ground.

3.2 Reader endorsement: criticism attracts the most endorsement, requests for help the least

This section answers the third question. The number of likes helps distinguish two things: how often a view is written, and how much that view is endorsed by other readers.

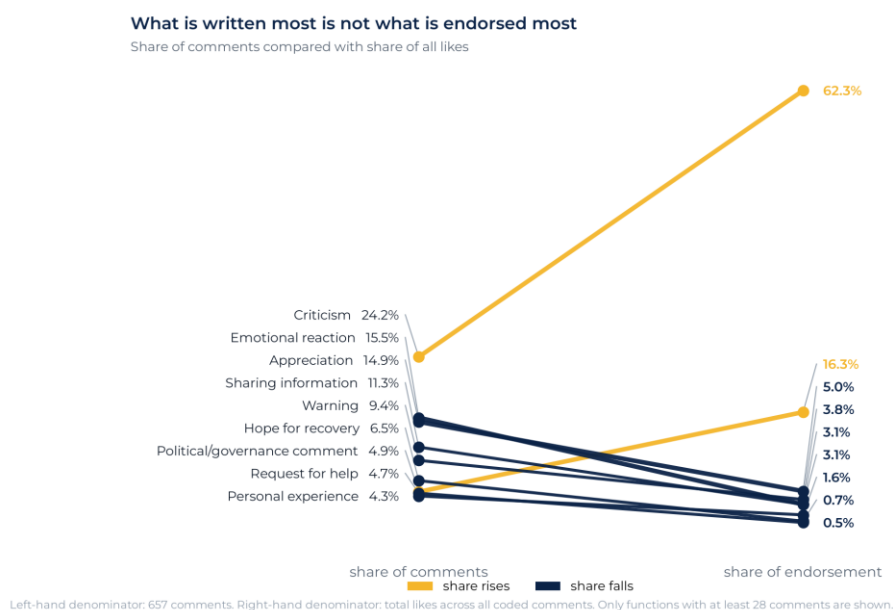


Figure 5. Share of comments compared with share of endorsement.

Criticism accounts for only 24.2 per cent of all comments but receives 62.3 per cent of all likes — a gap of 38.1 percentage points between the share of comments and the share of endorsement received. Conversely, appreciation accounts for 14.9 per cent of comments but only 5.0 per cent of likes. Requests for help account for 4.7 per cent of comments but only 0.5 per cent of likes. This chart is used to show how share shifts from the count of comments to the count of endorsements.

That difference is not necessarily caused by comment type alone. Criticism may appear more often on large posts read by many people. In addition, comments posted earlier have had longer to accumulate likes. Model 1 is used to check whether the difference in endorsement remains once these two factors are taken into account.

Table 1. Regression results. Figures in the table are coefficients (numbers showing the direction and size of a relationship in the model). Asterisks indicate statistical significance (how strong the evidence is that an observed relationship is not simply the product of variation in the data): * $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Standard errors are clustered at post level.**

Variable	Model 1	Model 2	Model 3
Function: political/governance comment	1.556***	—	—
Function: criticism	0.887**	—	—
Function: reporting conditions	0.216	—	—
Function: hope for recovery	-0.684**	—	—
Function: request for help	-0.829**	—	—
Log number of comments on the post	0.850***	0.334***	-0.182*
Time the comment has been visible (days)	0.018	—	—
Days since the main earthquake	—	0.046	0.069
Post by a citizen or local media account	—	-1.373***	0.990***
Observations	657	657	657
Post clusters	119	119	119
Pseudo R-squared	0.0980	0.0858	0.0475

Model 1 examines the factors associated with the size of reader endorsement. Once other factors are taken into account, political/governance comments have a positive coefficient, significant at the 1 per cent level (1.556). In this model their endorsement is about 4.7 times greater than that of emotional reaction (the reference category, or baseline). Criticism also has a positive coefficient, significant at the 5 per cent level (0.887), or about 2.4 times greater. Conversely, comments containing requests for help have a negative and significant coefficient (-0.829), with endorsement about 0.44 times that of emotional reaction. Comments expressing hope for recovery also point in a negative direction (-0.684).

Two other factors matter: post size and how long the comment has been visible. Time visible shows no significant relationship with the number of likes (0.018). The difference in endorsement is therefore not adequately explained by comments having sat longer in the comment section. Post size does matter, but once it is taken into account the differences between comment types remain visible. In this dataset, then, the size of endorsement is associated with the function of the comment, not only with when or where it appeared.

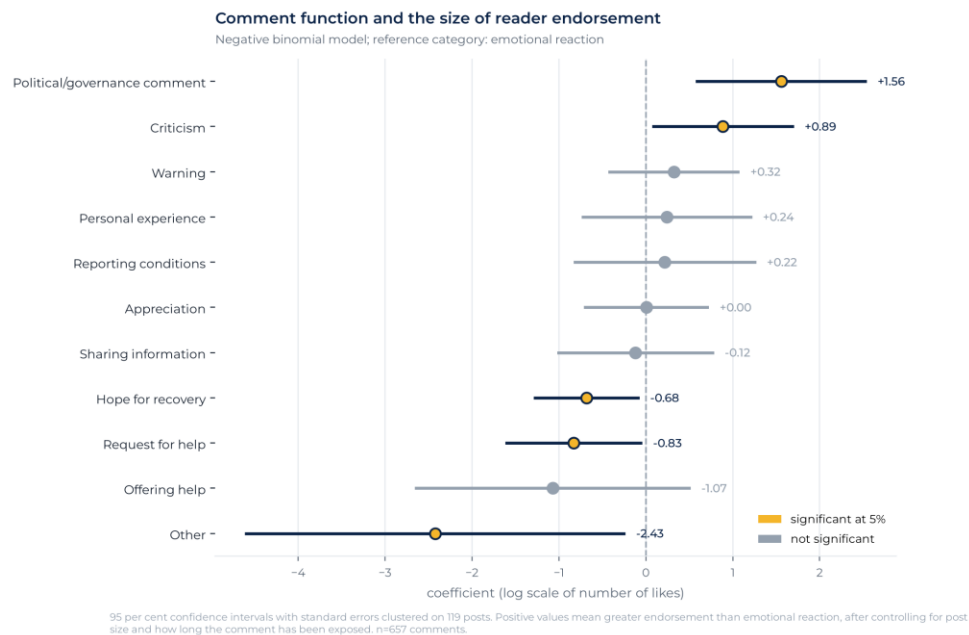


Figure 6. Model 1 coefficients by comment function, with 95 per cent confidence intervals.

3.3 Judgement of actors: those working in the field are judged positively, policy-makers considerably less so

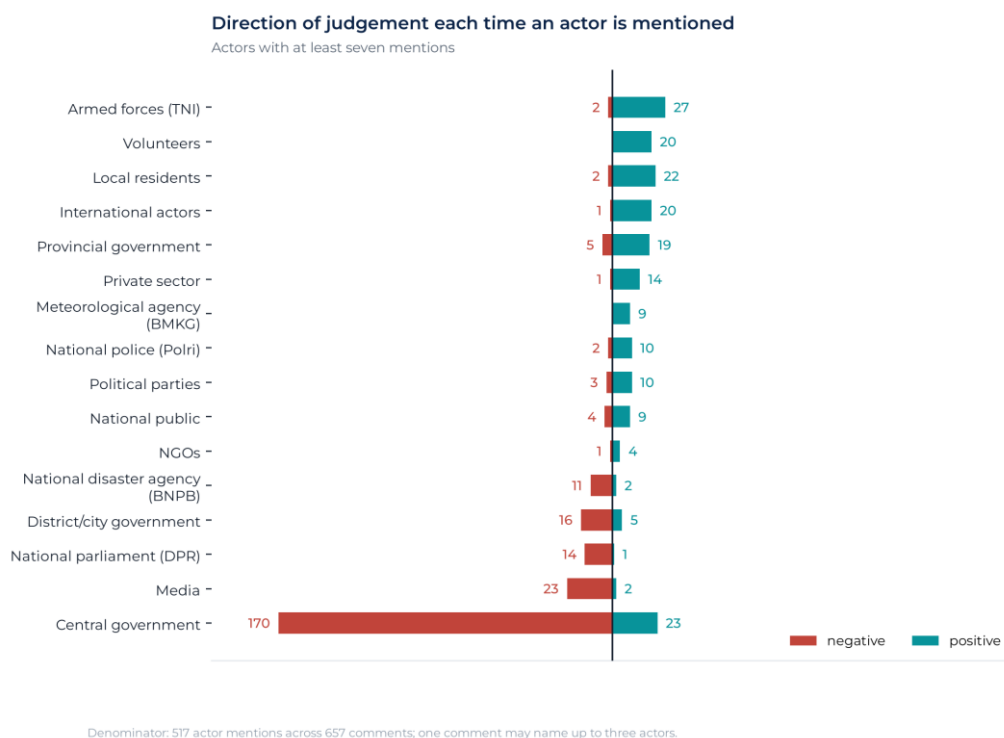


Figure 7. Direction of judgement each time an actor is mentioned.

Judgement of actors differs sharply according to their role. Actors working directly in the field are judged positively almost without exception: volunteers receive 20 positive judgements and none negative, the armed forces (TNI) 27 positive to 2 negative, and the meteorological agency (BMKG) 9 positive to 0 negative. Actors at the policy level, by contrast, are judged far more harshly: central government 23 positive to 170 negative, the national parliament (DPR) 1 to 14, and the national disaster agency (BNPB) 2 to 11. The dissatisfaction on display is therefore not a rejection of every state institution. Instagram users' judgements largely distinguish between the people and institutions working in the field and those who make or administer policy.

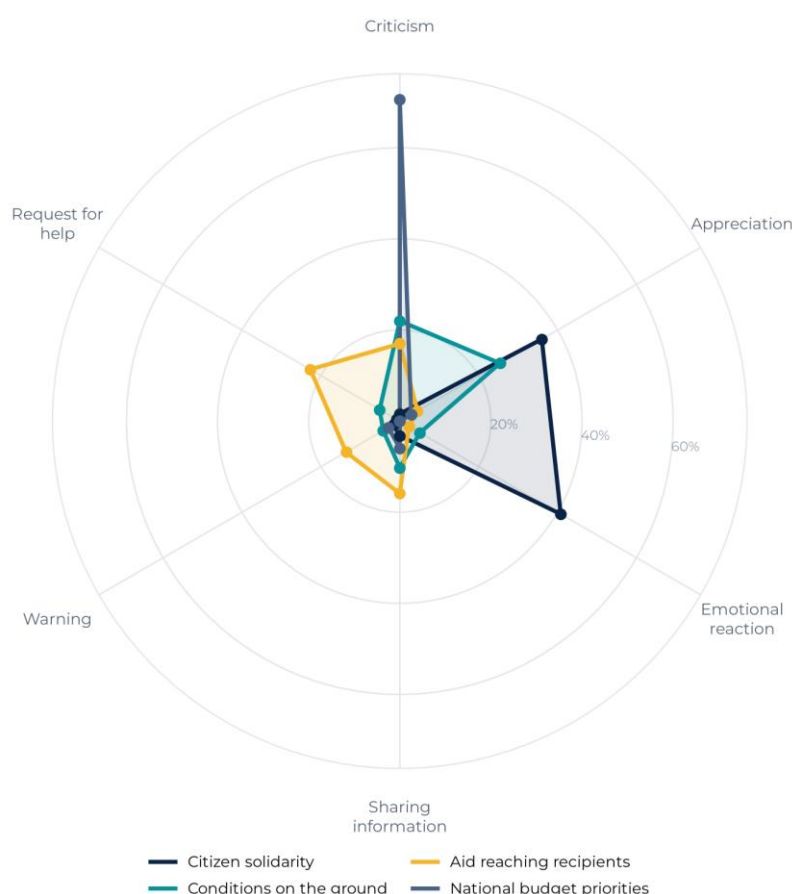
“One of the few agencies whose civil servants I will never snipe at. Thank you for your dedication.”

P012_C05, about BMKG – 188 likes · original: “Salah satu lembaga yg ASN.nya tidak akan aku nyinyirin. Terima kasih atas dedikasinya.”

3.4 How each discourse frame relates to comment function: every frame has its own characteristic shape

Each frame works in a different way

Composition of comment functions within the four largest frames



Each line sums to less than 100 per cent because the remaining functions are not shown. Denominators are the number of comments in each frame: Citizen solidarity 125, Conditions on the ground 118, Aid reaching recipients 88, National budget priorities 34.

Figure 8. Composition of comment functions within the four largest frames.

Each discourse frame has a different pattern of comments. The national budget priorities frame consists almost entirely of criticism and governance comment. The citizen solidarity frame contains far more emotional reaction and appreciation. The aid distribution frame sits between the two: alongside criticism it also carries warnings and requests for help. Because the shape of the conversation differs, the number of comments alone is not enough to understand its content and meaning.

3.5 Where the conversation happens shapes what it contains: comment sections on citizen and local media accounts carry less criticism and more solidarity

Models 2 and 3 examine whether the type of account a comment appears under is related to the content of the comment. On posts by citizen and local media accounts, the odds of a comment being criticism are significantly lower at the 1 per cent level (-1.373). Expressed more readably, the

odds are about 0.25 times those in other comment sections. Conversely, Model 3 shows that the solidarity frame appears more often in those spaces, about 2.7 times more than in other comment sections. The place where conversation occurs is therefore related to the kind of comment that becomes visible.

In Models 2 and 3 the unit “times” carries a slightly different meaning because both use logit regression. What is multiplied is not the number of likes but the odds — the ratio between the probability that a comment is criticism and the probability that it is not. A figure of 0.25 times means those odds fall to about a quarter, while 2.7 times means the odds of the solidarity frame appearing rise to about 2.7 times. Odds are not probabilities, so the figure cannot be read directly as a percentage.

A further test using a field-voice variable (combining reports of conditions, direct experience, and requests for help) shows no significant relationship ($p = 0.470$). Citizen and local media accounts are therefore not shown to carry more direct reporting from the disaster site. The difference lies mainly in the shape of the conversation: less criticism and more solidarity.

Model 2 also examines whether the content of the conversation changes over time, for example from expressions of grief towards judgement of performance. The coefficient for days since the main earthquake is not significant (0.046). In other words, the data do not support the supposition that such a shift occurred during the first week. Overall, the composition of the conversation was relatively stable across the observation period.

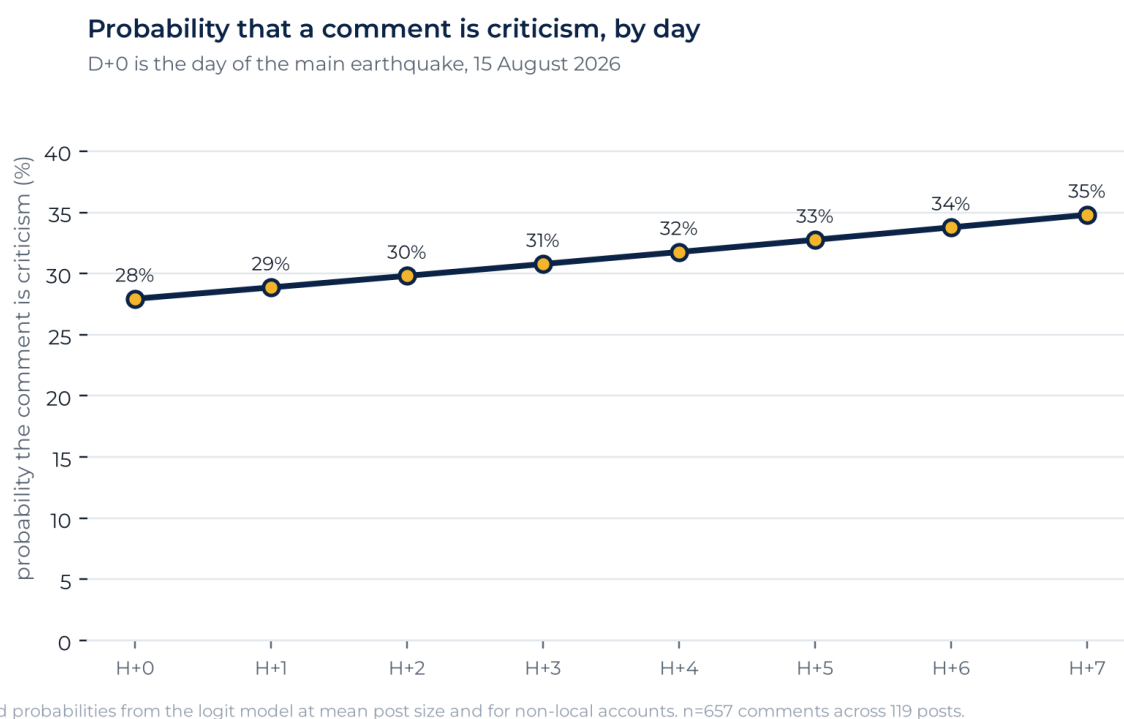


Figure 9. Predicted probability that a comment is criticism, by day.

3.6 What could not be answered: conditions on the ground and recovery were discussed too rarely to analyse

At the outset the study asked how conditions in East Nusa Tenggara were described, how people saw the recovery process, and whether judgements of present conditions related to expectations for the future. None of these three questions could be answered from the available data. Only 63 of 657 comments (9.6 per cent) genuinely described the condition of people, homes, or needs in East Nusa Tenggara. Only 2 comments (0.3 per cent) discussed the direction of recovery.

This is itself an important finding. A comment section is not a survey instrument: people come to react, not to file reports on conditions. The data were also collected seven days after the main earthquake, which is still too early for discussion of long-term recovery. The change in coding rules that produced these figures is explained in Section 4.

4. Limitations

A change in the research objective

At the pilot stage (an initial test of the method), the condition-assessment variable was filled in for 54 of 63 comments. On re-examination, most of those entries turned out not to be assessments of conditions at all. They were mostly judgements of officials' performance, expressions of sympathy, or requests for help. Because these are three different things, the coding rules were tightened. Fifty-three rows were revised and all subsequent coding used the new rules. The figures in Section 3.6 reflect the position after that correction.

Other limitations

- **Not the voice of the people of East Nusa Tenggara.** The data consist of Instagram user comments, some from East Nusa Tenggara and many from elsewhere. Affected residents who lost electricity, mobile signal, or devices are in fact harder to represent, because their access to social media may be limited.
- **Algorithmic visibility** (how Instagram's system decides which comments are easier to see) is a further limitation. Instagram displays comments by ranking, not by time order alone. Comments the system does not surface are consequently harder to find. This limitation arises from how the platform works and cannot be fully removed by research design.
- **Post selection bias** (the tendency of a sample to draw more heavily on certain kinds of post) also needs to be borne in mind. Because posts were selected by number of comments, the busiest posts entered the sample more easily and tend to be more political. Adding posts focused on conditions on the ground reduces this problem but does not eliminate it.
- **Campaign detection is also imperfect.** The automated system flagged 27 comments showing repeated message patterns, but manual reading still found similar patterns

that had slipped through. Two campaigns were found only through manual reading. The figure of 21.7 per cent non-organic content should therefore be understood as a lower bound (the minimum successfully identified), not a definitive measure of all non-organic content.

- **Coding was carried out by a single coder, so no inter-coder reliability measure (a measure of whether several coders would assign the same categories) is available. What is available is a cross-variable consistency check. That check found no problems across the full set of rows, and coding changes are documented in a revision log.**
- **Regression results show association, not causation. The sample is purposive and there is no random assignment. The results must therefore not be read as evidence that one type of comment causes the number of likes to be higher or lower.**
- **The study covers a window of only eight days. These findings therefore describe the conversation during the first week after the earthquake, not the whole of East Nusa Tenggara's recovery.**

5. Implications

The implications below are drawn directly from the patterns visible in the data. They focus on improving disaster monitoring and communication, so that they can be applied by agencies and others responding to disasters.

If monitoring is based on how much social media users endorse a comment, requests for help will not receive attention

Model 1 shows that requests for help receive the lowest endorsement once other factors are taken into account. If social media monitoring ranks comments only by popularity, attention will fall disproportionately on national budget disputes and less on residents naming needs

in a particular village or hamlet. Monitoring for disaster response should therefore read the content of comments, not only the number of likes.

Aid reporting should be measured at the point of receipt

Official announcements often use measures of aid dispatched, for example in tonnes, while residents more often see how many kilograms actually reached them. This difference in accounting can leave government and citizens feeling that they are discussing different things. Aid reporting should be traceable through to the point of receipt, so that the amount dispatched and the amount received can be compared clearly.

How state aid is labelled affects how it is received

In this dataset, the idea that state aid is an obligation of the state rather than a personal gift recurs and attracts high endorsement. Instagram users' objections relate more often to how that aid is named or presented than to the aid itself. Crisis communication should therefore give more emphasis to information about the aid and its receipt, and less prominence to individual officials.

Local conversational spaces deserve different treatment

Models 2 and 3 show that comment sections on citizen and local media accounts contain less criticism and more solidarity. Such spaces can serve as venues for two-way communication, where government bodies and institutions can provide information and receive responses from residents at the same time. Monitoring that targets only large

accounts therefore risks missing important local conversation.

Social capital is a capacity that is already available and working

Citizen solidarity is the factor most often named as helping. Comment sections also function as an informal aid channel: residents pass requests on to those thought able to help, survivors from other areas share their experience, and residents of neighbouring districts organise collective prayers. This existing community capacity can be connected to official aid and information systems.

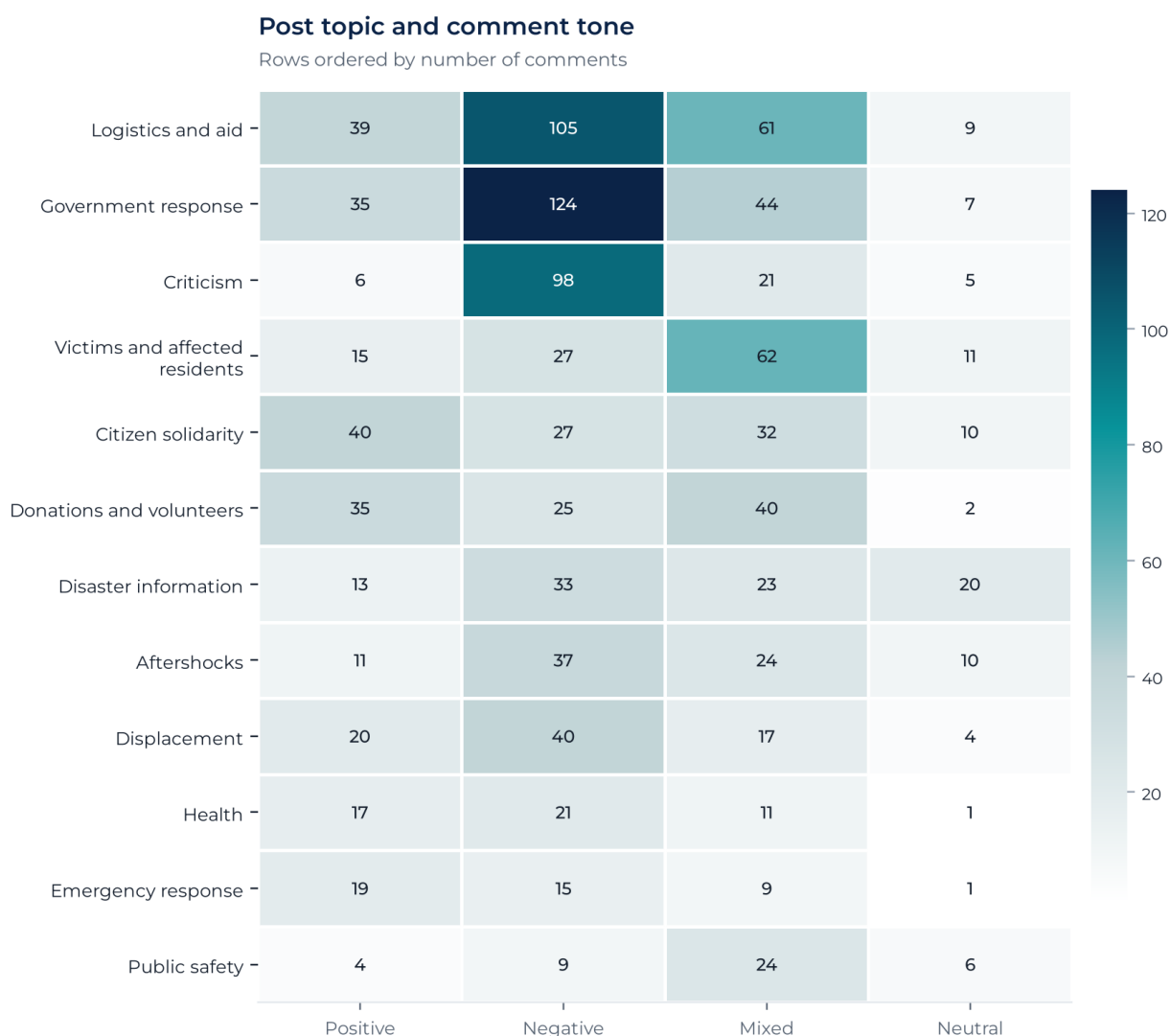
6. Conclusion

Public conversation about the East Nusa Tenggara earthquake in the first week was not solely negative. Three main layers appeared together. First, citizen solidarity. Second, highly concrete concern about aid that had not yet arrived, including named villages and quantities of aid. Third, debate about national policy. The third layer contains fewer comments, but comments of that kind attract far greater reader endorsement.

These three layers do not receive equal attention from Instagram's system or from readers. What is written most often is not necessarily what becomes most visible. Conversely, comments expressing immediate needs receive the least endorsement. If social media is used as a source of disaster information, this is the gap that requires attention: monitoring must search for needs by content, not by popularity alone.

Appendix A. Supporting charts

The charts below provide additional detail. They do not have to be read in order to follow the main argument of the report, but they can be used to examine the basis of each finding.



Topic is a multiple-response variable, so one comment may appear in more than one row. Denominator: 657 comments.

Figure 10. Post topic and comment tone.

Comment tone differs by post topic. Posts about government response and aid logistics attract a larger proportion of negative comments. Posts about citizen solidarity and affected victims, by contrast, attract more positive and mixed comments. Comment tone therefore depends not only on the attitude of Instagram users but also on the topic the post addresses.

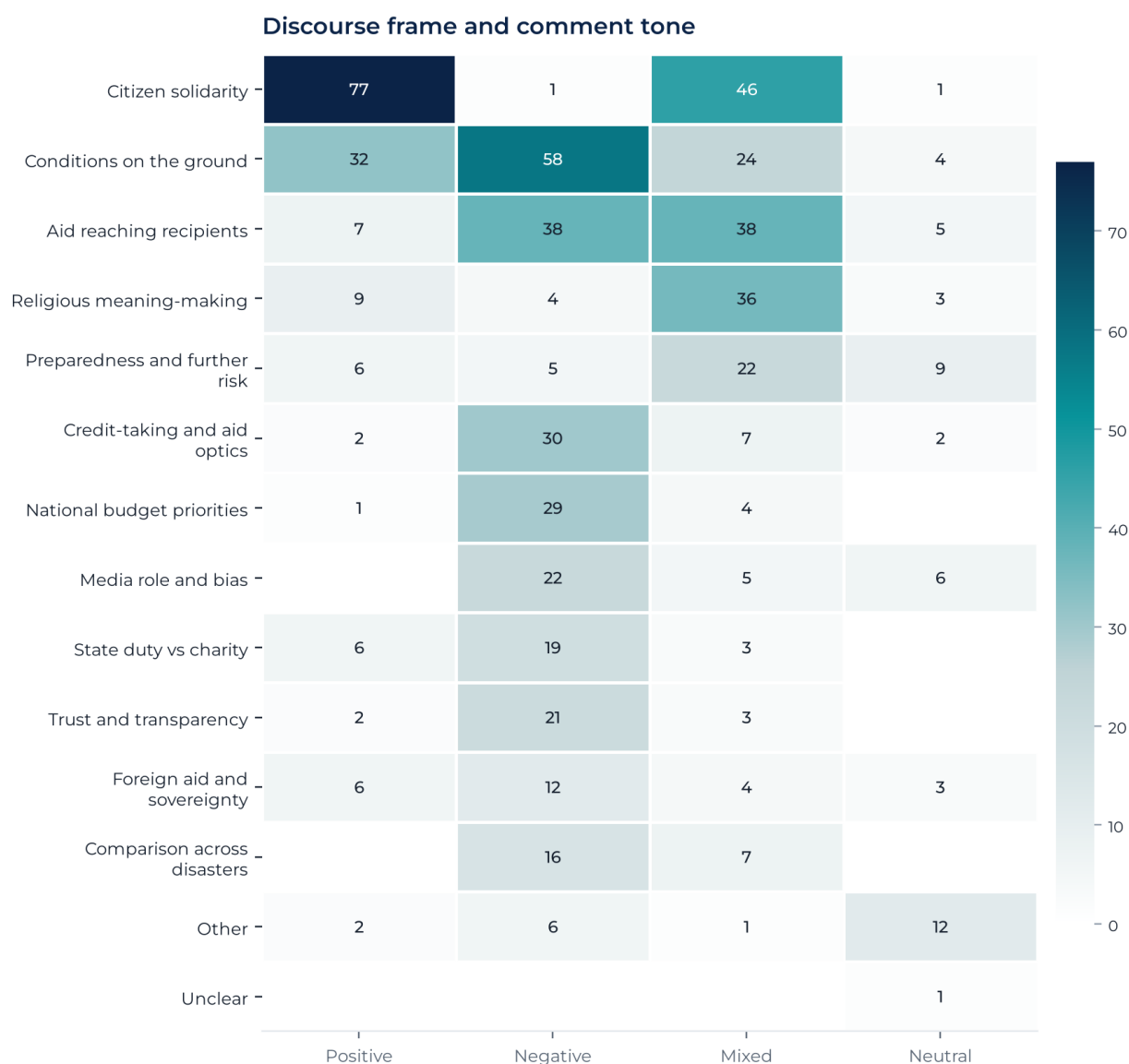


Figure 11. Discourse frame and comment tone.

This table shows that discourse frame and comment tone are two different things. The citizen solidarity frame is almost entirely positive or mixed in tone. The national budget priorities frame is almost entirely negative. The aid distribution frame, meanwhile, is split between negative and mixed comments. This pattern indicates that complaints about aid are often accompanied by the hope that delivery will improve.

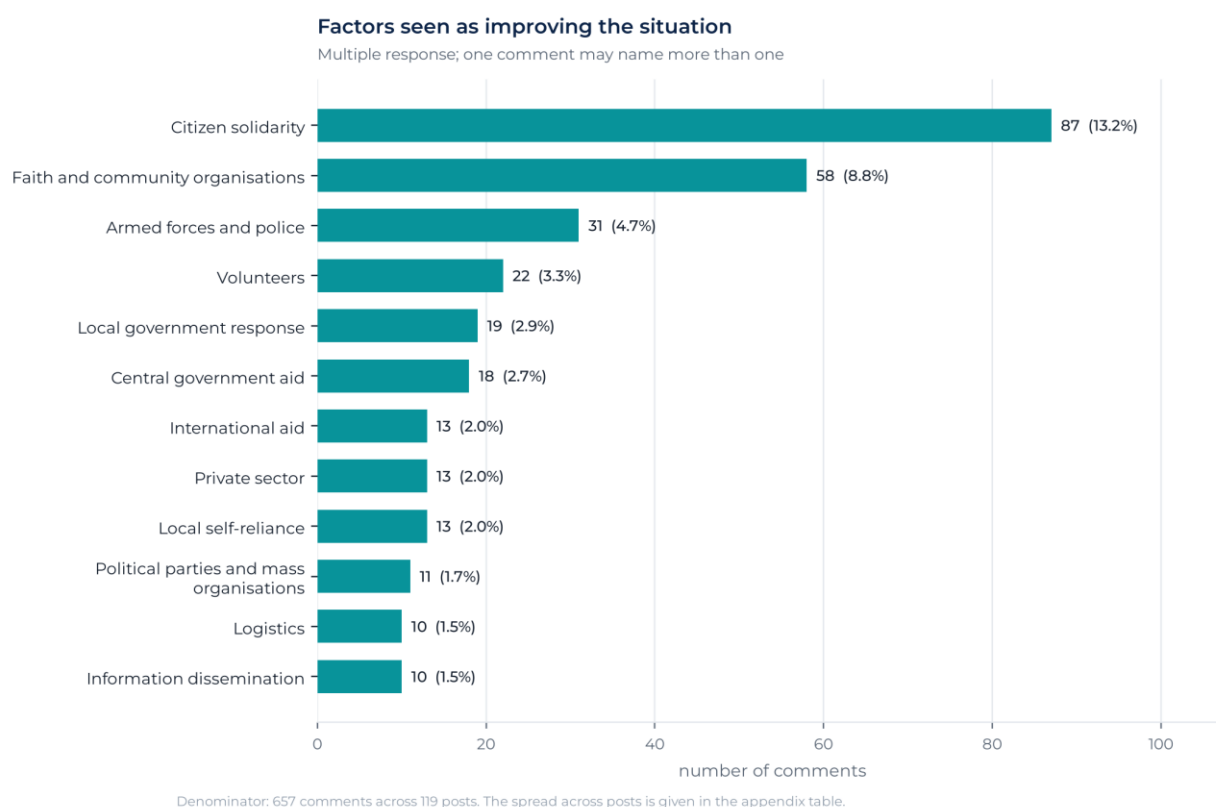


Figure 12. Factors seen as improving the situation.

Citizen solidarity is the factor most often named as improving the situation (87 comments). It also has the widest spread, appearing on 42.0 per cent of posts. Solidarity therefore appears not only in many comments but across many different posts. Faith and community organisations come second. Both of the top two factors originate in the community rather than in state institutions.

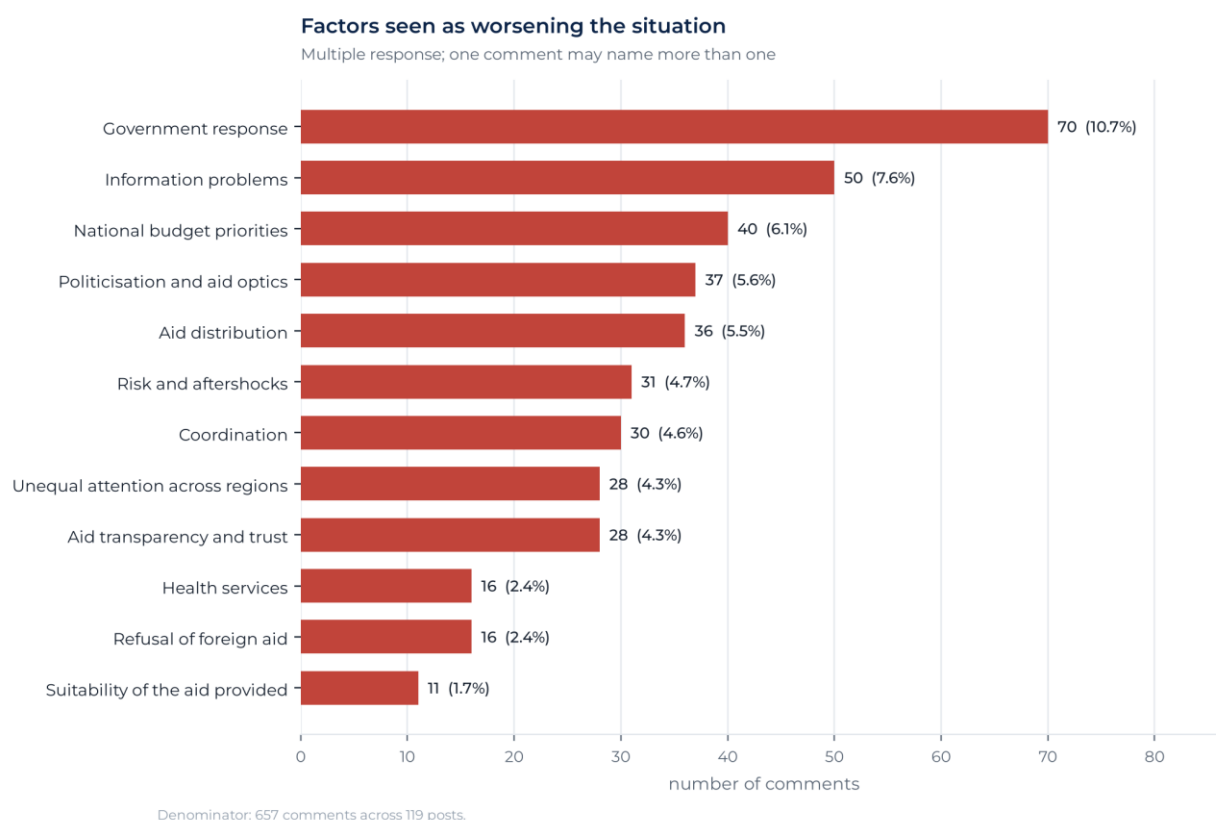
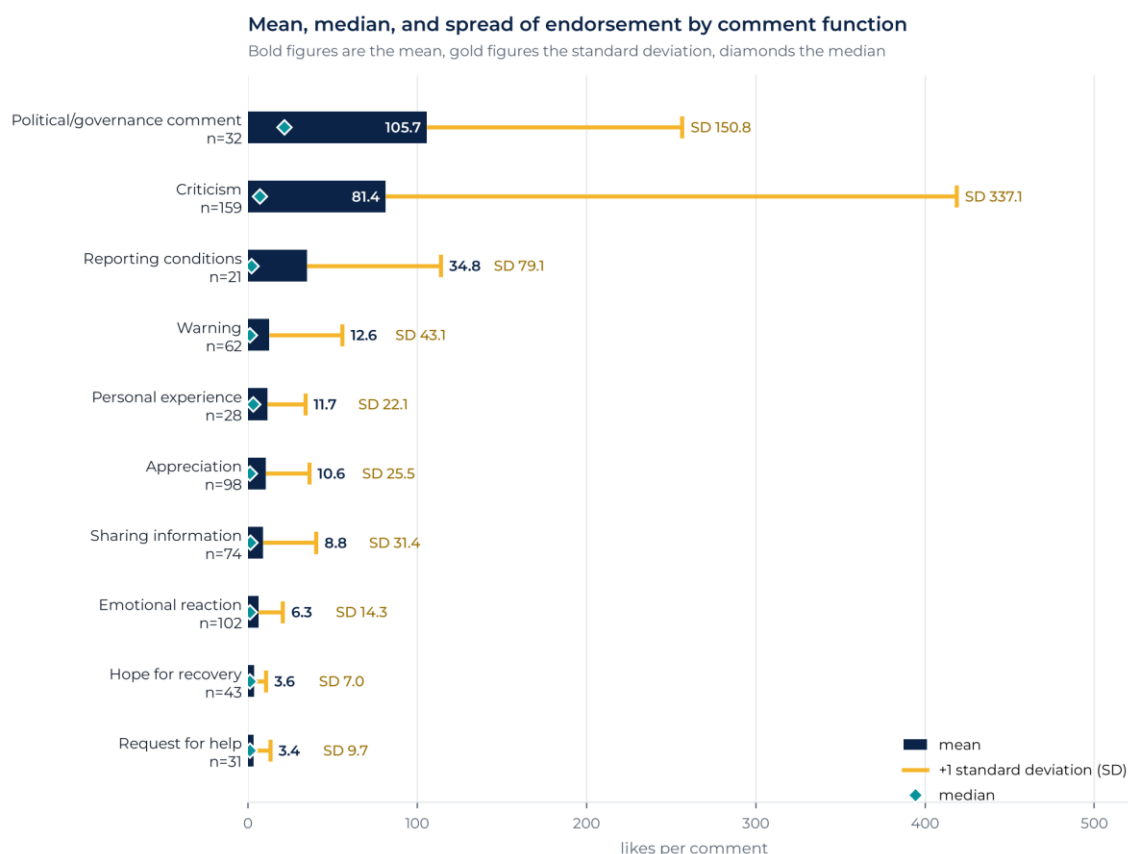


Figure 13. Factors seen as worsening the situation.

Government response is the factor most often named as worsening the situation (70 comments, spread across 33.6 per cent of posts). It is followed by information problems (50 comments) and national budget priorities (40 comments). The position of information problems is notable because part of the complaint concerns not the aid itself but whether information about that aid is considered clear and trustworthy.



In every group the standard deviation exceeds the mean, and the median always sits far below the mean. Both indicate a heavily skewed distribution: a small number of comments attract very large endorsement while most attract almost none. The main text therefore uses the median. A large standard deviation does not imply a large mean — criticism has a lower mean than political comment but a far wider spread. Denominator: 650 comments in functions with at least 20 comments.

Figure 14. Mean, median, and spread of endorsement by comment function.

The highest mean endorsement is found among political comments and criticism. However, the standard deviation (a measure of how far the data spread from the mean) is far larger than the mean in almost every group. This means the number of likes is highly uneven, and a single very popular comment can raise a group's mean sharply. The main discussion therefore uses the median (the middle value of the data), while this chart is retained to show the spread. It should be noted that a large standard deviation does not imply a large mean. Criticism has a lower mean than political/governance comment (81.4 against 105.7), but a far wider standard deviation (337.1 against 150.8). The chart therefore displays three figures at once: the mean as bar length, the standard deviation as a gold line, and the median as a diamond. The distance between median and mean shows how skewed each group is; for criticism, the median is only 7 likes while the mean is 81.4.

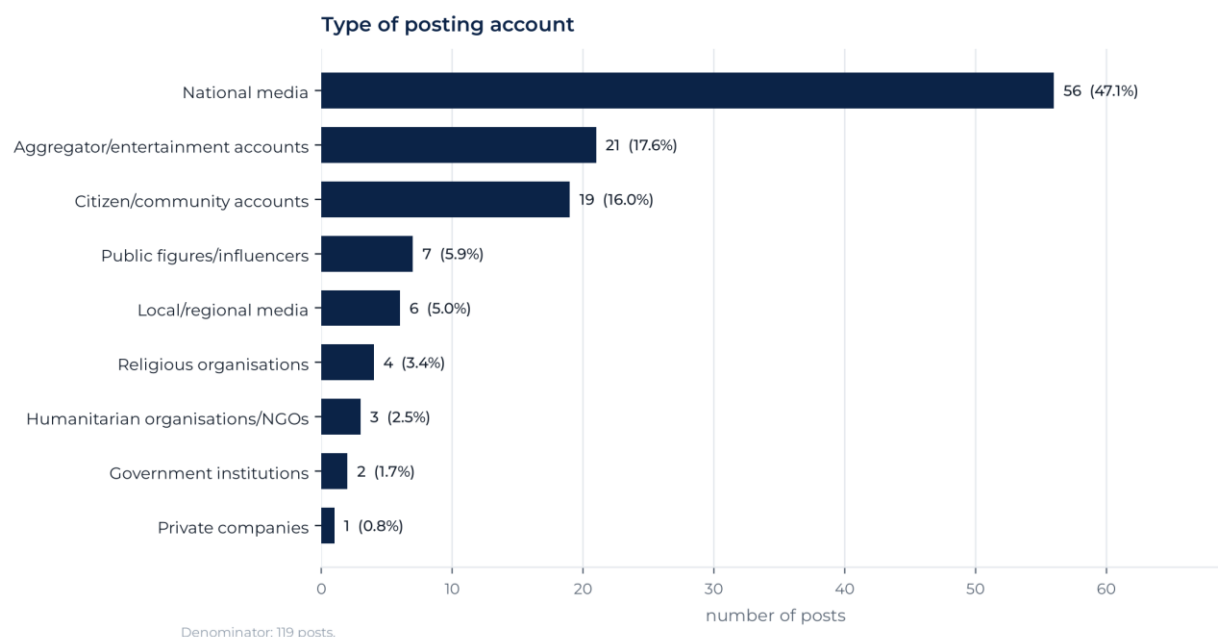


Figure 15. Type of posting account.

National media dominate the posts in the sample. This is a direct consequence of selecting the sample by number of comments. Posts by national media tend to attract more comments than posts by citizen accounts, so their chance of entering the sample is also greater.

Appendix B. Representative quotations

Quotations were selected from substantive comments (comments with enough content to analyse) coded with high confidence. One or two quotations were chosen for each discourse frame and ordered by number of likes. All quotations have been checked and confirmed as verbatim extracts from the original comments. Each quotation is given in English translation, with the original Indonesian reproduced beneath it so that the evidence can be verified.

Credit-taking and aid optics

“every route has to be polished up as Disney-like as possible”

P004_C01 – Criticism · original: “segala rute harus di poles se-disney mungkin”

“by the time he gets there: ‘I have received reports that the response has been good’”

P004_C07 – Criticism · original: “smp sana “sy mendapat laporan penanganan sudah baik””

Foreign aid and sovereignty

“but when outsiders want to help, it’s not allowed”

P004_C04 – Criticism · original: “giliran dr luar mau ngebantu gaboleh”

“Was it turned down on the spot by Prabowo?”

P010_C03 – Criticism · original: “Apakah lgsg ditolak sama prabowo?”

Aid reaching recipients

“Sent is not the same as distributed and received by the victims”

P022_C05 – Warning · original: “Dikirim tidak sama dengan di distribusikan dan diterima korban”

“They say there is plenty of aid, but when it arrives there is only a little”

P014_C02 – Reporting conditions · original: “Bilangnya bantuan banyak tp setelah datang hanya sedikit”

Trust and transparency

“Do not channel the aid through the government”

P025_C01 – Warning · original: “Bantuannya jangan di salurkan melalui pemerintah”

“Are you sure the donations actually arrive???”

P001_C01 – Criticism · original: “Yakin donasinya sampe???”

Preparedness and further risk

“A record for East Nusa Tenggara: 3,394 aftershocks”

P030_C01 – Reporting conditions · original: “Rekor NTT gempa susulan 3394”

“it is already around 4,000 notifications, thudding away, from us here”

P012_C03 – Reporting conditions · original: “su 4000an notif jedag jedug dari kami”

State duty vs charity

“It is not aid.. It is the government’s obligation”

P002_C04 – Political/governance comment · original: “Bukan bantuan.. Itu kewajiban pemerintah”

“eiger: 100 – govt: -11”

P017_C01 – Criticism · original: “eiger: 100 - govt: -11”

Conditions on the ground

“They are still traumatised, sir. Their houses are all damaged too”

P007_C08 – Reporting conditions · original: “Mereka masih trauma pak. Rumah mereka juga sdh pada rusak”

“all talk, without ever going down to the site itself”

P007_C02 – Criticism · original: “hanya tau bacot tanpa turun ke lokasi kejadian langsung”

Other

“People still throw rubbish anywhere”

P049_C02 – Warning · original: “Buang sampah masih sembarang”

“Where did this happen?”

P020_C02 – Sharing information · original: “Kejadian dimana ini yah ?”

Religious meaning-making

“save our brothers and sisterssss”

P045_C01 – Emotional reaction · original: “selamatkan saudara saudari kamiii”

“O God, protect all our brothers and sisters over there”

P024_C01 – Emotional reaction · original: “Ya allah lindungin semua sodara2 disna”

Media role and bias

“let me bookmark this — usually someone turns up later to explain themselves till they are blue in the face”

P017_C03 – Criticism · original: “tandain dulu ahh ntar biasanya ada yg klarifikasi sampai berbusa mulutnya”

“The TV channels only started reporting once it was already bad, and social media users spread it first”

P032_C02 – Criticism · original: “TV TV mulai ikut memberitakan setelah udh parah & lebih dlu warganet yg sebarakan”

Comparison across disasters

“It reminds me of SBY during the tsunami, going straight from Papua to Aceh”

P004_C06 – Political/governance comment · original: “Jadi ingat SBY saat tsunami dulu, dari papua langsung berkeras ke Aceh”

“A country at war can still help other nations. How are things here in Indonesia?”

P010_C02 – Political/governance comment · original: “kondisi lagi perang masih bisa bantu negara lain. Di indonesia gmn kabarnya?”

National budget priorities

“When Paris feels closer than Flores”

P004_C02 – Criticism · original: “Ketika Paris terasa lebih dekat dibandingkan Flores”

“We demand that the asset forfeiture bill be passed sooner”

P009_C01 – Political/governance comment · original: “Kami minta percepat saikan UU perampasan aset”

Citizen solidarity

“Beaten to it by the white-haired one”

P004_C05 – Criticism · original: “Kalah cepet sama si rambut putih”

“only Mr Ganjar understands ordinary people”

P006_C01 – Appreciation · original: “hanya pak Ganjar yg mengerti rakyat kecil”

The logo for 'Impact cannot Wait' is located in the bottom left corner. It consists of a black square with the words 'Impact cannot Wait' in white, stacked vertically.

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Email: impactcannotwait@gmail.com
Website: <https://icw-steel.vercel.app/> (temporary domain)