RESEARCH ARTICLE

Message Framing, Emotional Reactions, and Engagement Intention Toward AI-Generated Art Content on Social Media: A Between-Subjects Experiment Among Indonesian Emerging Adults

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ABSTRACT

Social media platforms in Indonesia have become central spaces for public debate about contested emerging technologies such as AI-generated art. This study investigates how message framing, benefit, threat, and neutral framings of AI-generated art, influences post-exposure emotional reactions and engagement intentions among Indonesian emerging adults. A between-subjects vignette experiment was conducted with 165 Indonesian emerging adults aged 18 to 29 years, randomly assigned to one of three framing conditions; following manipulation check and attention check exclusions, the final analytic sample was N = 94 (36 Benefit, 33 Threat, 25 Neutral). Emotional reactions were measured using the validated Indonesian Positive and Negative Affect Schedule (PANAS; Watson et al., 1988; Akhtar, 2019), and engagement intention was measured using four behavioral intention items. Prior attitude and pre-exposure emotional baseline were entered as covariates in all analyses of covariance (ANCOVA). Threat framing significantly increased negative affect, $F(2, 89) = 6.541$, $p = .002$, $\eta^2p = .128$, and significantly suppressed positive affect relative to the other two conditions, $F(2, 89) = 5.27$, $p = .007$, $\eta^2p = .106$. Positive affect was strongly correlated with engagement intention, $r(92) = .572$, $p < .001$, whereas negative affect showed no association, $r(92) = -.022$, $p = .833$. Framing had no direct effect on engagement intention once prior attitude was controlled; prior attitude emerged as the strongest predictor of engagement intention, $\eta^2p = .285$, explaining approximately 29 percent of its variance. These findings indicate that message framing shapes emotional response, but positive affect specifically, rather than negative arousal, is the primary psychological pathway to engagement behavior on social media.

Keywords: *AI-generated art, engagement intention, emotional reactions, message framing, postive affect, social media*

ABSTRAK

Platform media sosial di Indonesia telah menjadi ruang utama perdebatan publik tentang teknologi baru yang kontroversial seperti seni yang dihasilkan kecerdasan buatan (AI). Penelitian ini menginvestigasi bagaimana framing pesan, manfaat, ancaman, dan netral terhadap seni yang dihasilkan AI, memengaruhi reaksi emosional pasca-paparan dan intensi keterlibatan pada dewasa awal Indonesia. Eksperimen vignette between-subjects dilakukan dengan 165 dewasa awal Indonesia berusia 18 hingga 29 tahun yang secara acak ditugaskan ke salah satu dari tiga kondisi framing; setelah penerapan kriteria eksklusi manipulation check dan attention check, sampel analitik akhir adalah N = 94 (36 Benefit, 33 Threat, 25 Neutral). Reaksi emosional diukur menggunakan Positive and Negative Affect Schedule (PANAS) versi bahasa Indonesia yang tervalidasi (Watson dkk., 1988; Akhtar, 2019), dan intensi keterlibatan diukur menggunakan empat item intensi perilaku. Sikap awal dan baseline emosional pra-paparan dimasukkan sebagai kovariat dalam seluruh analisis kovarians (ANCOVA). Framing ancaman secara signifikan meningkatkan negative affect, $F(2, 89) = 6{,}541$, $p = {,}002$, $\eta^2p = {,}128$, dan secara signifikan menekan positive *affect dibandingkan kedua kondisi lainnya, $F(2, 89) = 5,27$, $p = ,007$, $\eta^2p = ,106$. Positive affect berkorelasi kuat dengan intensi keterlibatan, $r(92) = ,572$, $p < ,001$, sedangkan negative affect tidak menunjukkan hubungan, $r(92) = -,022$, $p = ,833$. Framing tidak memiliki efek langsung terhadap intensi keterlibatan setelah mengontrol sikap awal; sikap awal muncul sebagai prediktor terkuat dari intensi keterlibatan, $\eta^2p = ,285$, menjelaskan sekitar 29 persen variansinya. Temuan ini menunjukkan bahwa framing pesan membentuk respons emosional, tetapi positive affect secara khusus, bukan negative arousal, merupakan jalur psikologis utama menuju perilaku keterlibatan di media sosial.*

Kata Kunci: *seni yang dihasilkan AI, intensi keterlibatan, reaksi emosional, framing pesan, positive affect, media sosial*

INTRODUCTION

The rapid development of digital communication technologies has fundamentally transformed how individuals receive, interpret, and engage with information. As of early 2024, Indonesia recorded approximately 185.3 million internet users, representing 66.5 percent of the total population, with 64.8 percent of adults aged 18 and above actively using social media (DataReportal, 2024). These platforms do not merely distribute content; they amplify it. Platform algorithms determine which posts gain visibility based on engagement signals such as likes, reposts, replies, and shares, creating feedback loops in which content that provokes stronger behavioral responses receives progressively greater reach (Metzler & Garcia, 2024). Unlike traditional mass media, in which audiences were receivers of one-directional content, social media constitutes a fundamentally bidirectional communication environment in which users actively interact with and amplify content (Mangold & Faulds, 2009). Understanding what drives audience emotional reaction and subsequent engagement is therefore a matter of direct consequence for how information and controversy spread across Indonesian digital discourse.

Among the platforms shaping this discourse, X (formerly Twitter) occupies a distinctive position. Although its registered user base is smaller than platforms such as Instagram or TikTok in absolute numbers, an estimated 25.2 million Indonesians used X as of January 2025, approximately 12 percent of the national adult population (DataReportal, 2025), and the platform functions as a uniquely consequential space for real-time public debate. Kwak et al. (2010), in the first large-scale quantitative study of the entire Twitter network, established that the platform operates not merely as a social network but as a news medium, with topics circulating with exceptional speed across its structure. X's predominantly text-based format, in contrast to the visually dominant formats of Instagram or TikTok, also makes it particularly well suited for studying message framing specifically, since it avoids confounding a textual manipulation with the emotional influence of accompanying video or image content.

A defining characteristic of this environment is that the textual construction of a message, not merely its topical content, shapes how audiences respond to it. This is the central concern of message framing: the strategic selection and emphasis of certain aspects of an issue in order to promote a particular problem definition, causal interpretation, moral evaluation, or treatment recommendation (Entman, 1993). AI-generated art provides a timely example of a genuinely contested issue suited to this kind of manipulation: that AI-powered tools now enable anyone with internet access to produce professional-quality visual art without a photographer or studio can be framed as a democratizing creative opportunity accessible to all, or as an act of economic and moral harm against working human artists. Both framings may draw on accurate factual claims; what differs is which aspects are foregrounded and what emotional response they are designed to invite. Empirical research confirms that AI-generated art is perceived ambivalently across audiences: Doshi and Hauser (2024) found that access to generative AI ideas increased individual creative productivity but simultaneously reduced the collective diversity of creative output, while Zhou and Lee (2024), analyzing over four million artworks, found that adopting text-to-image AI tools substantially increased artists' productivity and audience reception. This authentic ambivalence, real benefits alongside real concerns about homogenization and displaced creative labor, makes AI-generated art a genuinely contested rather than one-sided issue, well suited to a framing manipulation.

Research has consistently demonstrated that message characteristics systematically influence engagement behaviors such as reposting, replying, and liking (Cha et al., 2010; Suh et al., 2010; Vosoughi et al., 2018), which in turn increase a post's algorithmic visibility (Metzler & Garcia, 2024). Brady et al. (2017), in a large-scale analysis of Twitter discourse on contested political topics, found that moral-emotional language substantially increases the rate at which messages are retweeted. Vosoughi et al. (2018) further established, in an analysis of approximately 126,000 news stories shared on Twitter, that emotionally novel and provocative content diffuses significantly farther and faster than neutral content. The pathway through which framing influences engagement runs primarily through emotional response. According to appraisal theory (Lazarus, 1991), emotions arise from individuals' cognitive evaluations of what a message implies for their personal goals and concerns; different appraisal patterns produce distinct discrete emotions, with appraisals of unjustified harm caused by an identifiable agent producing anger, and appraisals of threat combined with low coping potential producing fear (Smith & Ellsworth, 1985).

Nabi's (1999) cognitive-functional model elaborates this distinction by differentiating approach-oriented negative emotions, such as anger, which motivate active behavioral engagement and information-seeking, from avoidance-oriented negative emotions, such as fear, which motivate withdrawal. Critically, this model does not predict that a threat frame automatically produces anger: an appraisal of unjustified harm attributed to an identifiable, addressable agent biases the response toward the approach-oriented pathway, whereas a threat appraised as diffuse or lacking a clear locus of responsibility is more likely to produce the avoidance-oriented pathway instead. This appraisal is also conditioned on personal relevance (Lazarus, 1991): a threat to artists' livelihoods is most directly relevant to practicing or aspiring artists, whereas general social media users without a personal or professional connection to the creative industries may appraise the same threat as more distant, potentially muting the predicted emotional response. The behavioral economic tradition provides further grounding for the predicted asymmetry across framing conditions: Tversky and Kahneman (1981) demonstrated through prospect theory that losses are weighted more heavily than equivalent gains, implying that loss-framed (threat) messages should generate a stronger psychological reaction than gain-framed (benefit) messages.

Despite this substantial theoretical grounding, empirical work directly testing the framing-emotion-engagement pathway for a genuinely contested emerging technology issue, using a topic where public opinion is still forming rather than already polarized, remains limited, particularly within the Indonesian social media context and among Indonesian emerging adults specifically. Emerging adults, broadly defined as individuals aged 18 to 29 (Arnett, 2000, 2004), represent one of the most digitally active demographic segments in Indonesia and occupy a distinctively bidirectional role in the information ecosystem: unlike earlier generations who were primarily receivers of media content, today's emerging adults routinely both consume and redistribute it, meaning their emotional reactions to framed content do not stay private but actively shape what subsequent audiences encounter. Prior Indonesian research further supports the relevance of this population: Meuthia et al. (2023) found that frequent social networking site use among Indonesian adolescents and emerging adults was associated with distinct patterns of empathic responding, and Andangsari et al. (2024) similarly reported that emotional reactivity and dysregulation predicted problematic internet use specifically on X among this population, together suggesting that emotional responses to framed content may function as especially consequential predictors of engagement among Indonesian emerging adults. This study therefore examines how benefit, threat, and neutral framings of AI-generated art shape post-exposure emotional reactions (positive and negative affect) and engagement intention among Indonesian emerging adults, testing the following hypotheses.

H1: Message framing will significantly influence emotional reactions, such that (a) framing will significantly influence negative affect, and (b) framing will significantly influence positive affect, consistent with appraisal theory (Lazarus, 1991) and Nabi's (1999) cognitive-functional model. H2: Emotional reactions will be significantly associated with engagement intention, such that (a) positive affect will be significantly correlated with engagement intention, and (b) negative affect will be significantly correlated with engagement intention, based on evidence that emotional arousal drives online engagement behavior (Brady et al., 2017; Valenzuela et al., 2017). H3: Message framing will significantly influence engagement intention directly, such that engagement intentions will differ significantly across the three framing conditions, drawing on framing theory (Entman, 1993) and loss aversion under prospect theory (Tversky & Kahneman, 1981).

METHOD

Research Design

This study employed a single-factor, between-subjects experimental design with three conditions: benefit framing, threat framing, and neutral framing. Using standard experimental notation (Neuman, 2014), the design is represented as R O_1 O_2 X_1 O_3 O_4 O_5 (Benefit), R O_1 O_2 X_2 O_3 O_4 O_5 (Threat), and R O_1 O_2 X_3 O_3 O_4 O_5 (Neutral), where R is random assignment, O_1 is pre-exposure prior attitude, O_2 is pre-exposure PANAS (emotional baseline), X_{1-3} are the framing stimuli, O_3 is the post-exposure manipulation check, O_4 is post-exposure PANAS, and O_5 is post-exposure engagement intention. A between-subjects design was chosen because it eliminates order effects that would arise from within-subject comparison of multiple frames, mirrors naturalistic social media exposure in which a user typically encounters one version of a post at a time, and reduces demand characteristics (Shadish et al., 2002). All three stimulus versions shared an identical base text, factual statistics, account name, post length, and accompanying AI-generated product image, differing only in framing-specific content, so that any observed differences are attributable to the framing manipulation alone. Pre-exposure PANAS scores were entered as covariates rather than used to compute change scores, since this approach avoids the reliability attenuation associated with subtracting correlated measurements while achieving equivalent statistical control (Vickers & Altman, 2001; Field, 2018).

Participant

The target population was Indonesian emerging adults aged 18 to 29 who were active users of X or a comparable short-form social media platform, defined consistent with industry usage metrics (DataReportal, 2024) as regularly browsing and reading content at least once weekly, without requiring an active posting history. Participants were recruited through convenience and snowball sampling via personal social media networks. An a priori power analysis using G*Power 3.1 (Faul et al., 2009) for a one-way ANCOVA with three groups, medium effect size ($f = 0.25$; Cohen, 1988), $\alpha = .05$, and power = .80, indicated a minimum required sample of $N = 159$. Random assignment to condition was implemented using NimbleLinks, a third-party link-randomization service, since Google Forms, the survey platform used, does not natively support randomizing respondents across different form versions; a single distributed link redirected participants with approximately equal probability to one of three separately hosted condition-specific forms.

Data collection yielded 165 complete responses across the three conditions. Because a substantial proportion of responses failed the manipulation check (43 percent overall, ranging from 33 percent in the Benefit condition to 54 percent in the Neutral condition) or the attention check, these cases were excluded following the procedure specified in advance, yielding a final analytic sample of $N = 94$ (36 Benefit, 33 Threat, 25 Neutral). A sensitivity power analysis conducted on this corrected N indicated that the study could reliably detect effects of Cohen's $f \geq .33$ at 80 percent power.

Measures

Emotional reaction was measured using the full 20-item Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) in its validated Indonesian state version (Akhtar, 2019), administered before and after stimulus exposure using the instruction "How do you feel right now?", rated on a five-point scale. Engagement intention was measured using four behavioral intention items assessing the likelihood of liking, reposting, replying to, and sharing the stimulus post, adapted from Alhabash and McAlister (2015) and Valenzuela et al. (2017) and rated on a seven-point Likert scale; a composite score was computed as the mean of the four items. Prior attitude toward AI-generated art was measured using four semantic differential items on seven-point bipolar scales following Ajzen's (2006) approach to constructing bipolar attitude scales. The manipulation check used a direct recognition format following Perdue and Summers (1986): immediately after reading the stimulus, participants identified which type of message (benefit, threat, or neutral) they believed they had just read, with three response options corresponding to the three conditions.

Data Analysis

Prior to hypothesis testing, descriptive statistics and assumption checks were conducted, including tests of normality (Shapiro-Wilk), homogeneity of variance (Levene's test), and baseline equivalence across conditions (one-way ANOVA on pre-exposure measures). Hypotheses were tested using one-way analysis of covariance (ANCOVA) with framing condition as the independent variable, prior attitude and the relevant pre-exposure PANAS subscale as covariates, and Tukey-corrected post hoc comparisons to probe significant main effects (Field, 2018). The association between emotional reactions and engagement intention was tested using Pearson product-moment correlations. All analyses were conducted using Jamovi 2.6.26 with a significance threshold of $\alpha = .05$, two-tailed.

RESULTS

Baseline equivalence checks confirmed that random assignment produced statistically equivalent groups prior to stimulus exposure: prior attitude, $F(2, 56.7) = 0.909$, $p = .409$; pre-exposure positive affect, $F(2, 51.9) = 2.099$, $p = .133$; and pre-exposure negative affect, $F(2, 55.2) = 0.281$, $p = .756$, did not differ significantly across the three conditions. Descriptively, post-exposure positive affect was highest in the Benefit condition ($M = 3.75$), intermediate in Neutral ($M = 3.48$), and lowest in Threat ($M = 3.21$), while post-exposure negative affect was highest in Threat ($M = 3.12$) relative to Benefit ($M = 2.61$) and Neutral ($M = 2.68$).

Testing Hypothesis 1a, framing condition significantly affected post-exposure negative affect, $F(2, 89) = 6.541$, $p = .002$, $\eta^2 p = .128$, supporting H1a with a medium effect size. The Threat condition produced significantly higher negative affect than both Benefit and Neutral, consistent with the theoretical prediction that threat framing activates approach-oriented negative affect. Testing Hypothesis 1b, framing condition also significantly affected post-exposure positive affect, $F(2, 89) = 5.27$, $p = .007$, $\eta^2 p = .106$, supporting H1b. Tukey-corrected post hoc comparisons showed that positive affect was significantly higher in Benefit than Threat (mean difference = 0.379, $p = .024$) and significantly higher in Neutral than Threat (mean difference = 0.452, $p = .014$), while Benefit and Neutral did not differ significantly from each other ($p = .885$), indicating that threat framing specifically suppressed positive affect relative to both other conditions.

Testing Hypothesis 2, post-exposure positive affect was strongly and significantly correlated with engagement intention, $r(92) = .572$, $p < .001$, supporting H2a with a large effect. Post-exposure negative affect showed no meaningful association with engagement intention, $r(92) = -.022$, $p = .833$, and H2b was therefore not supported. Testing Hypothesis 3, framing condition had no significant direct effect on engagement intention once prior attitude was controlled, $F(2, 90) = 0.748$, $p = .476$, $\eta^2 p = .016$; H3 was not supported. Prior attitude toward AI-generated art, however, was a highly significant covariate across models, most notably in the engagement intention model, $F(1, 90) = 35.800$, $p < .001$, $\eta^2 p = .285$, accounting for approximately 29 percent of the variance in engagement intention and emerging as its single strongest predictor across all analyses.

DISCUSSION

This study examined how benefit, threat, and neutral framings of AI-generated art shape post-exposure emotional reactions and engagement intention among Indonesian emerging adults. Three of five hypotheses were supported (H1a, H1b, H2a) and two were not (H2b, H3), a pattern that is theoretically informative precisely because it is mixed.

Message framing significantly shaped both negative and positive affect, with threat framing producing the highest negative affect and the lowest positive affect relative to the other two conditions. This is consistent with appraisal theory and Nabi's (1999) cognitive-functional model, though the medium rather than large effect size is worth interpreting alongside this study's boundary conditions. The threat stimulus described harm to "human artists" as a collective, diffuse group without naming a specific company, platform, or actor responsible, which may have limited the intensity of the predicted approach-oriented response, since Nabi's model attributes anger specifically to appraisals of harm caused by an identifiable, addressable agent. Relatedly, because AI-generated art is most personally relevant to individuals who work in creative industries, general social media users without such a connection may have appraised the threat as comparatively distant, further moderating the emotional response. It is also notable that the suppression of positive affect occurred specifically in the threat-versus-other-conditions comparison, with threat framing proving more emotionally potent in disrupting existing positive states than benefit framing was in generating new ones, a pattern broadly consistent with the negativity bias literature, in which negative information exerts disproportionate influence on emotional states relative to equivalent positive information (Rozin & Royzman, 2001).

The most crucial finding was the large positive correlation between post-exposure positive affect and engagement intention, providing strong support for the appraisal-based theoretical pathway at the core of this study: positive emotional experience, rather than negative arousal, appears to be the primary psychological driver of engagement behavior on social media. The near-absence of association between negative affect and engagement intention is consistent with the possibility that the PANAS negative affect subscale, a composite aggregating anger, fear, and other discrete emotions, may have masked a more specific effect of anger alone, since anger rather than fear is the emotion most associated with approach-oriented engagement. It is also possible that self-reported engagement intention is itself a weaker proxy for actual behavior under negative emotional states specifically. This study relied on Kim and Yang's (2017) finding that self-reported behavioral intentions on social media correspond closely with actual platform behaviors to justify engagement intention as a valid proxy measure; however, a single supporting citation is a narrower evidentiary basis than this assumption requires, particularly since that correspondence may not hold equally well across emotional states, a possibility that warrants direct behavioral validation in future research.

The absence of a direct effect of framing on engagement intention, alongside the dominant role of prior attitude, suggests that pre-existing evaluative dispositions toward AI-generated art matter considerably more for behavioral engagement than the framing of any single message encountered. This is consistent with the elaboration likelihood model (Petty & Cacioppo, 1986), which predicts that for issues about which individuals hold strong prior attitudes, pre-existing evaluative orientations dominate behavioral intention formation while peripheral message cues such as framing play a comparatively minor role; AI-generated art appears to be precisely such an issue for Indonesian emerging adults, who held strong and heterogeneous prior attitudes toward the topic. This is consistent with meta-analytic evidence that framing effects in naturalistic settings tend to be real but limited in magnitude once prior attitudes are accounted for (Amsalem & Zoizner, 2022). Notably, the pattern of results across H1b, H2a, and H3, a significant effect of framing on positive affect, a significant association between positive affect and engagement intention, and a non-significant direct effect of framing on engagement intention, is consistent with what a full mediation model would predict: that framing's influence on engagement intention operates indirectly through positive affect. The present analyses tested these relationships as separate models rather than as a single mediation model; because all necessary variables were collected within the same dataset, a formal bootstrapped mediation analysis is recommended as a priority for future research building on this design.

Several limitations qualify these conclusions. The single-exposure, cross-sectional design captures responses at one point in time and cannot establish whether effects would persist or accumulate with repeated exposure, as occurs in naturalistic social media use (Amsalem & Zoizner, 2020). All dependent and control variables relied on self-report, introducing the possibility of social desirability bias. A topic familiarity item was designed as an additional covariate but was inadvertently omitted from the deployed survey instrument, preventing its inclusion in the reported models. A substantial proportion of collected responses (43 percent) failed the manipulation check, reducing the final sample below the a priori target and producing unequal cell sizes across conditions (36, 33, and 25); a sensitivity analysis indicated the study remained adequately powered to detect the medium-to-large effects that were found, though smaller effects underlying the non-significant results cannot be ruled out. Finally, this study did not distinguish between participants with a personal or professional connection to the creative industries (e.g., practicing artists) and those without, a distinction that appraisal theory suggests may moderate the personal relevance, and therefore the emotional intensity, of the threat framing.

CONCLUSION

This study finds that message framing meaningfully influences emotional reactions toward social media posts about AI-generated art among Indonesian emerging adults: threat framing significantly increased negative affect and significantly suppressed positive affect relative to the other conditions. Positive emotional reactions were strongly associated with engagement intention, whereas negative emotional reactions showed essentially no association. Message framing did not directly influence engagement intention once prior attitude was controlled, and prior attitude toward AI-generated art emerged as the strongest predictor of engagement intention across all analyses. These findings suggest that for contested emerging technology topics in the Indonesian social media context, message framing shapes emotional response, but positive emotional experience specifically, rather than negative arousal, is the primary psychological pathway to engagement behavior, and audiences' pre-existing attitudes toward a topic matter considerably more than the framing of any single message they encounter. Future research should prioritize formal mediation testing, discrete-emotion measurement, and pilot testing of stimulus materials to verify manipulation strength before full-scale data collection.

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