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I cue you liking me: Causal and spillover effects of technological engagement bait

Wanjiang Jacob Zhang, Jingjing Yi, Hai Liang [*]

School of Journalism and Communication, The Chinese University of Hong Kong, Hong Kong

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ABSTRACT

Baiting user engagement is pervasive on social media platforms, and new strategies and tools have been developed to facilitate this engagement bait. However, the empirical effects and theoretical mechanisms are rarely examined. The present study formally explicates engagement bait based on the concept of cues and illustrates a strategy for luring user engagement in computer-mediated communication. Furthermore, combining matching and within-between models, we tested the causal effect of engagement bait on encouraging user engagement on a Chinese video-sharing platform, Bilibili, with a random sample of 188,249 users and their 1,810,787 videos. In addition to the significant direct effect on the bait-using video, our findings suggest a spillover effect that applying technological engagement bait can increase engagement with the bait user's other videos even if these videos did not use the bait function.

1. Introduction

Engagement bait is a prevalent yet frequently unnoticed phenomenon in daily life. It encompasses various instances such as the "exclusive!" headlines in news websites, the "share this if you're an Aries!" posts on social media or click-through ads in different mobile apps. All these share a common objective: to motivate recipients to engage in specific activities, particularly by taking automatic action. With the advancements in media technologies, a plethora of engagement baits have emerged online, allowing bait senders to profit from generating various forms of engagement, such as clicks and likes (Potthast et al., 2018). The majority of prior studies have adopted the concept of clickbait in their investigation of this phenomenon. Clickbait is defined as a strategy that entices clicks through attractive and misleading content (e.g., Chakraborty et al., 2016; Lu & Pan, 2021). However, clickbait is a concept that pertains to a specific technique currently in use, which does not apply to emerging techniques that may not ask for or rely on clicks. In this study, we propose a broad concept of engagement bait and a sub-concept called technological engagement bait, which relies on technological cues (Sundar, 2008; Xu & Liao, 2020). We also use causal inference to test the direct and spillover effects of technological engagement bait in the context of computer-mediated communication (CMC).

Engagement bait is a strategy that intentionally urges the receivers to interact with the media content, user, or interface through digital engagement actions. Technological engagement bait is a kind of engagement bait that only relies on technical features, such as navigation hyperlinks and interactive buttons. These forward-looking concepts can explain current occurrences as well as potential future phenomena, which assists us in addressing the fundamental question in CMC – "how and whether new technologies affect the utility of theories that were developed in the context of somewhat older technological contexts" (Walther, 2011, p. 470).

Moreover, we propose to apply the concept of cues in CMC to explicate engagement bait. As is common in many persuasive communications (Fransen & Fennis, 2014), engagement bait uses cues as fundamental elements to reinforce its effects. Apart from social signals and message elements, technological affordances can also act as cues to impact user engagement (Sundar, 2008; Xu & Liao, 2020) by triggering heuristics through their presence (e.g., navigation buttons) or operational metrics (e.g., the number of likes) (Sundar et al., 2015). By introducing the concept of cues, we bridge the gap between research on clickbait, engagement bait, and CMC theories. This shift in focus has moved beyond the practical goal of improving click-through rates of news or ads (Kuiken et al., 2017; Robinson et al., 2007) and detecting abusive baits on the internet (Naeem et al., 2020), towards a more

* Corresponding author. School of Journalism and Communication, Room 310, Humanities Building, New Asia College, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong.

E-mail address: hailiang@cuhk.edu.hk (H. Liang).

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comprehensive understanding of their underlying nature, effects, and mechanisms. Furthermore, this perspective paves the way for exploring how emerging technological forms shape people's perceptions, behaviors, and relationships with technology.

We further tested the causal effect of technological engagement bait, which includes direct effects, increasing engagement in bait-using objects (e.g., videos), and spillover effects, increasing engagement in objects published by the same author without baits. In terms of theoretical significance, verifying the effectiveness of technological engagement bait can address a crucial issue in media and technology research: whether the new technologies are merely a channel of transmitting information between senders and receivers (Sundar et al., 2015). Testing the effects of technological engagement bait, particularly the spillover effect, can help us rethink the intrinsic value of technology, which can shape CMC independently of the effects of source and message. However, previous studies have not yielded consistent findings regarding whether technological cues in engagement bait can generate more engagement (e.g., Hou, 2017; Molina et al., 2021). This study can provide empirical evidence to fill this gap. In terms of practical significance, by gaining a deeper understanding of its effects, platforms can improve their ability to detect and regulate the spread of low-quality information, leading to a healthier platform ecosystem and a more positive user experience. Content producers can benefit from this knowledge by responsibly utilizing baits to increase their content engagement.

Nevertheless, testing the effects of technological engagement bait is a challenging task. Previous studies on technological cues were mostly conducted in laboratories (e.g., Kim & Gambino, 2016; Molina et al., 2022) and their applicability needs to be retested in real-world settings. More importantly, spillover effects cannot be found in experiments where each subject is independent. However, isolating the effects of technological bait from other factors in real-world settings is difficult. To address this, this study collected a random sample from Bilibili, a Chinese video-sharing website, and employed matching and within-between modeling to conduct causal inference based on observational data. Multiple robustness tests were conducted to validate the effects of technological engagement bait.

2. Theoretical background and hypothesis development

2.1. From clickbait to engagement bait

Before Facebook's announcement that it would fight engagement bait (Silverman & Huang, 2017), advertising and journalism studies had noticed the tendency to use bait, especially clickbait, in digital media. For example, different kinds of online advertisements want to increase the crucial metric of click-through rate (CRT) through clickbait to lead users to a web page (Robinson et al., 2007). In journalism, clickbait is a strategy of structuring the "effective headline" to increase news clicks (Kuiken et al., 2017). In particular, it features attractive and misleading content that draws readers in and arouses their curiosity to entice them to click (Zhang & Clough, 2020). Several studies have examined clickbait detection (Chakraborty et al., 2016; Jain et al., 2021), and found that clickbait is effective in increasing CRT (Kuiken et al., 2017), enhancing political propaganda (Lu & Pan, 2021), and lowering perceptions of credibility and quality (Molyneux & Coddington, 2020).

However, the widely used concept of clickbait is scope-limited and time-bound. First, clickbait only applies to baits specifically designed for CRT and does not include any other forms of engagement such as comments, shares, votes, or tags. Additionally, it only applies to baits that require clicking behaviors, such as clicking on links or buttons, and does not cover other actions like dragging, sliding, or zooming. Second, it does not apply to baits emerging with future technologies. To address this issue, this study proposed the concept of engagement bait, which is defined as a strategy that intentionally urges the receivers to interact with the media content, user, or interface through digital engagement actions (e.g., likes, shares). Compared with clickbait, engagement bait can cover various bait approaches and interactive activities on digital media, which maintains lasting explanatory power for potential new forms. As such, clickbait is a type of engagement bait that utilizes click features to increase CRT. The differences between the two concepts are shown in Table 1.

2.2. Engagement bait and technological engagement bait based on cues

Many prior studies on clickbait have concentrated on detecting it, which is a practical purpose with limited theoretical concern (Bronakowski et al., 2023; Potthast et al., 2016). This study introduces the concept of engagement bait, not only to enhance its detection, but also to gain a more profound comprehension of its nature, effects, and mechanisms from a theoretical perspective. Within the framework of CMC, we posit that engagement bait can be explicated by the concept of cues. A cue, broadly speaking, indicates a particular social meaning that is decoded by the receiver in interpersonal communication (Burgoon, 1991). In the context of digital media use, we follow Sundar's (2008, p. 79) definition of a cue as anything "that might serve as a trigger for the operation of a heuristic," where heuristic refers to a mental shortcut judgment rule based on stored memory and knowledge (Chaiken, 1980). Accordingly, engagement bait refers to the production of cues to stimulate users to engage with the media object through triggering heuristics.

Xu and Liao (2020) classified four types of cues to help us understand engagement bait: social signals, social categories, message elements, and technological affordances. Social signals are non-verbal communication signals (e.g., facial expression, voice tone) in the biological and physical dimensions that convey useful information based on environmental or cultural context (Fiore et al., 2013; Rice, 1992). These non-verbal cues are enabled by visual technologies in CMC. For example, a YouTuber can make a thumbs-up gesture to signal the audience to like the video.

Social category cues can notify observers of the identity of the sender or the source of the information. According to the social identity model of deindividuation effects (SIDE; Spears & Postmes, 2015), cues can facilitate the group identification process in CMC, and these group cues could influence attitudes and behaviors. Consequently, engagement bait often includes group cues, such as "Share or You're Not Chinese!" or "Like the Post if You Are an Aries!"

Message elements in CMC such as language style, emoji, font style, or hashtags also serve as cues, especially when nonverbal cues were hard to replicate in the early stage of media technology (Walther et al., 2015). These cues are common in clickbait headlines with an exaggerated language style or a large "SHOCK!!!" label (Zhang & Clough, 2020). Social media users also tend to add emojis in their posts to increase user engagement (McShane et al., 2021).

Table 1
Differences between clickbait and engagement bait.

	Clickbait	Engagement Bait
Definition	A way of structuring headlines and online content to generate but not fulfill readers' curiosity so readers are compelled to click to obtain more information (Lu & Pan, 2021). Catchy headlines accompanying the article links, which lure the readers to click on the links (Chakraborty et al., 2016).	A strategy that intentionally urges the receivers to interact with the media content, user, or interface through digital engagement actions.
Bait target	Click-through rate (CRT) and clicks.	Any engagement behaviors and metrics: e.g., likes, comments, shares, bookmarks, tags, votes.
Bait form	Mainly text-based, e.g., structuring headlines, attractive/misleading words.	All forms of baits, including text, image, or technological features (e.g., buttons, links).
Scope of Discipline	Specific concept in journalism and advertising.	General concept for all fields.

Finally, cues emerge in the form of technological affordances in digital media. Affordances are technological attributes of interactive media to trigger user actions and cue user perceptions (Sundar et al., 2015). Through customization, individual users can utilize and tailor technological affordances which contain different technological cues to influence their audience. For instance, a simple navigation hyperlink or interactive button can be used as engagement bait to entice viewers to interact without any verbal or physical cues. It is important to note that these four types of cues are not mutually exclusive (Xu & Liao, 2020), and engagement bait can use one or several cues in different forms.

Based on the last category, cues as technological affordances, this study further defined technological engagement bait as a distinct form of engagement bait that solely relies on technical features (e.g., interactive buttons) and the technological cues embedded in it. Technological cues can activate different heuristics and behaviors in receivers, technological engagement bait solely comprises cues that stimulate their engagement-related heuristics and actions. As Xu and Liao (2020) summarized, cues generated in various ways (e.g., by humans or technologies) can result in different levels of social presence – "the degree of salience of the other people in the interaction" (Short et al., 1976, p. 65). In the context of CMC, social presence indicates the psychological state of the audience to perceive virtual (para-authentic or artificial) social actors as actual social actors through the richness of human-related elements (Lee, 2004). From this perspective, technological engagement bait is in a low level of social presence. It uses technological cues without human-related elements to shape receivers' actions, such as interactive buttons or popularity metrics that reflect the number of interactions (Sundar, 2009). Thus, the effects of technological engagement bait are attributed to the interactive technologies of the medium rather than the source or message of the communication.

2.3. *Effects of technological engagement bait on user engagement*

Engagement refers to the behavioral and psychological experience of communicating via media with four critical components: physical interaction, interface assessment, absorption, and digital outreach (Oh et al., 2018). This study focuses on engagement in the behavioral dimension, which includes physical actions like clicking and digital outreach behaviors like bookmarking for future use. These user engagement behaviors are observable and commonly reflected in interaction metrics in digital media. Moreover, even though behavioral engagement and psychological engagement capture different aspects, they are closely correlated (Oh et al., 2018). In other words, engagement behaviors are likely to occur if technological engagement bait results in positive evaluations and absorption of the interface or content.

Engagement bait stimulates users' engagement behaviors because of the cues embedded in it. For example, clickbait will depend on stylistic features, which is a kind of message element cue, to attract attention and increase clicks (Kuiken et al., 2017). According to the cues-filtered-out approach (Culnan & Markus, 1987), many nonverbal cues in face-to-face settings are reduced in CMC, which decreases communication quality and effectiveness. By contrast, Walther and his colleagues (Walther, 1996; Walther et al., 2005) argue that verbal cues in written messages are interchangeable and equivalent to nonverbal cues to help individuals process information in CMC. Both verbal and nonverbal cues can be found in baits with human-related elements, and their effectiveness has been well-studied (e.g., Kuiken et al., 2017; Walther et al., 2018). In addition, individuals can make use of any cues that are available in a given communication setting (Walther et al., 2015) in which the cues are not only the reproduction of social reality but also the creation of media technology (Couldry & Hepp, 2018). Nevertheless, most previous studies examining the effects of technological cues have been conducted using experimental designs with limited external validity (Kim & Gambino, 2016; Molina et al., 2022), necessitating further testing in real-world settings. Moreover, inconsistencies in findings have been observed in previous studies regarding the ability of technological cues in technological engagement bait to generate more engagement (Hou, 2017; Molina et al., 2021). To fill this gap, this study empirically tested the effects of technological engagement baits on user engagement in a video-sharing website.

2.3.1. *Direct effect of technological engagement bait*

Sundar et al. (2015) developed the TIME model, which conceptualizes the technological attributes of interactive media as affordances. They conducted several studies to examine how these affordances shape communication outcomes through two routes: the action route and the cue route. They consistently found that technological engagement bait also affects the audience's engaging actions through these two routes.

In the action route, technological engagement bait can add modality interactivity to increase user engagement. Modality interactivity refers to the various interaction methods afforded by the medium that promotes user engagement by expanding users' perceptual bandwidth. By the same token, the interactive features on the interface bring "more and different sensory channels" involved in user interactions (Reeves & Nass, 2000, p. 65). Several studies have shown that higher levels of website interactivity generate more cognitive engagement (Guillory & Sundar, 2014), behavioral engagement (Xu & Sundar, 2014), and more positive interface assessment (Oh & Sundar, 2015). Therefore, it is plausible that individual users who adopt the strategy of adding modality interactivity, such as inserting an interactive button, can encourage other users to interact with them or their content.

In the cue route, technological engagement bait can trigger various heuristics to affect the audience's assessment of the content and lead to interaction behaviors. There are two main ways for technological affordances to trigger heuristics as cues, which are: by their presence and "by adaptively gathering information for the user in the form of metrics" (Sundar et al., 2015, p. 70). Presence means that using a certain technological feature is the message to transmit cues. For example, the same content was perceived as more credible when viewed through a touch-screen device than a traditional mouse-controlling device because the novel device transmitted the positive heuristics of coolness and novelty (Oh et al., 2013; Sundar et al., 2015). Similarly, bait users can apply the latest stylish functions to boost audience evaluation and interaction. Meanwhile, the helper heuristic will be triggered if content creators improve the navigability affordances by adding hyperlinks or "useful" buttons. Through expression affordance such as commenting buttons, bait users can affect receivers' political attitudes, increase perceived interactivity, and encourage them to discuss politics (Wang & Sundar, 2022). Notably, some negative heuristics, such as intrusiveness and distraction, can be triggered by the purposive pop-up bait and inhibit engagement (Diao & Sundar, 2004).

In sum, technological engagement bait can trigger various heuristics that might lead to engagement behaviors. Given these arguments, we propose the first hypothesis:

H1. Using technological engagement bait will directly increase user engagement with the content.

2.3.2. *Spillover effect of technological engagement bait*

The direct effect on user engagement with specific content does not fully capture the impact of technological engagement bait. In other words, it may influence engagement with other content created by the same author, even if the bait is not applied. We propose this effect as the spillover effect, which is explained in two possible ways.

First, more people will interact with message senders who increase engagement with bait-using content. According to the bandwagon effect, a high number of likes and views indicates the popularity of the content, which leads to positive perceptions and conformity behaviors (Waddell & Sundar, 2020). Meanwhile, many media platforms promote user-generated content based on metrics of likes or shares. By using engagement bait in a single post or video, content creators can increase their exposure, which motivates other users to visit their personal pages and engage with their other content.

Second, users' prior engagement with the bait-using content will predict their future engagement with the same creator. Previous studies (Lim et al., 2015; Zhang et al., 2017) show that engagement with the channel or company can increase user loyalty and stickiness. Even though the engagement might be enticed by bait, this behavior can build and strengthen the link between the content creator and the audience to encourage future engagement. Moreover, users' previous interactions with the author can be gathered and presented, which enhances the perceived interactivity. For instance, in live-streaming rooms or video-sharing websites, viewers who interact with the online streamer or video uploader will receive fan badges, which are upgraded along with continued engagement. This perceived interactivity cues the contingency heuristic to motivate users' future participation (Lee & Park, 2013).

To conclude, technological engagement bait may present an extended effect on other users and a long-lasting effect on users' future actions, which implies an increase in engagement with other content from the same author. Nevertheless, the spillover effect has been rarely examined because it is challenging to observe it in previous experiments where the subjects are independent. This study proposes the second hypothesis and tests it through within-between models based on observational data in real-world settings:

H2. Technological engagement bait will increase user engagement with other content from the same creator.

3. Method

This study tested the effects of engagement bait on Bilibili, a Chinese online video-sharing platform, following the introduction of a new feature that enables content creators to incorporate an interactive bar with three buttons into their videos (see Appendix A). This interactive bar is a kind of bullet chat[2] posted by the video uploaders rather than the audience. Specifically, this bar contains three interaction buttons (like, favorite, and drop-coin[3]) to the video, which appears 5 seconds into the video and then disappears. Viewers can click any of three buttons to perform the corresponding engagement or long-press the like button to complete all three kinds of engagement at once when watching the video. Bilibili calls this bar the "triple hits" ("sanlian" in Chinese) button, meaning one click to conduct three kinds of engagement. Video uploaders can decide whether to use the "triple hits" bar in each of their videos. This bar is a technological cue that enhances the audience's perceptual bandwidth (Sundar et al., 2015). As such, we considered videos that utilized the "triple hits" bar as utilizing technological engagement bait.

3.1. Sample and data collection

We first created a sampling frame of all Bilibili users, that is, the list containing all user IDs, to get a random sample of Bilibili uploaders. Each registered user has a unique ID composed of numbers, which is generated incrementally by Bilibili based on the sequence of users' registration time; a larger ID number denotes a more recent registration time. However, Bilibili's ID sequence is not a simple list with continuous integers, which means that there is an uncertain interval greater than zero between any two users' IDs that may result from some unknown reasons like account deletion or Bilibili's ID generation algorithm. However, neither the total user number nor the ID range nor the algorithm has been officially disclosed by Bilibili.

This study thus designed a Python program to explore the distribution of user IDs. We registered a new Bilibili account on Feb 24, 2022, and got a 10-digit ID which implied the upper limit digit of existing user IDs. Then, we created a function to generate a 10-digit number (1–9,999,999,999) and requested the Bilibili API (http://api.bilibili.com/x/space/acc/info?mid=) to check whether the user ID exists. The maximum ID we got was "2147471639" after we looped this function 10,054,885 times. We thus used a more precise range (1–2,500,000,000) to conduct efficient ID searching. Finally, we got 24% (6,958,080) registered users from 28,914,540 random-generated IDs. Uploaders were identified as Bilibili users who published at least one video. We used another Bilibili API (https://api.bilibili.com/x/space/arc/search?mid=) to check the published list of each user. Users who have not published videos were excluded from the dataset. Ultimately, our sample includes 188,249 uploaders who published 1,810,787 videos in total. All the uploader-level (e.g., sex, verification status, account level) and video-level (e.g., duration and topic) data were collected at the same time through the Bilibili API.

3.1.1. Matching

Among the 188,249 uploaders in our dataset, 4140 applied the "triple hits" function bar at least once in their videos. This resulted in an extreme imbalance between the treatment and control groups, which may cause a notable reduction in statistical power when estimating the treatment's effects (van Belle, 2008). Therefore, we utilized matching to adjust the dataset. Matching refers to any techniques used to balance the distribution of covariates in the treated and control groups. It aims to closely replicate a randomized experiment by selecting well-matched samples from the original observational datasets, thus helping to reduce bias caused by the covariates (Stuart, 2010). It is a preprocessing step to estimate the treatment effect before other analytical methods like regression.

Given the nature of our datasets, we selected coarsened exact matching (CEM) as the most appropriate matching method among the various options available. CEM is an improved version of the most ideal matching method named exact matching (EM). EM aims to find identical samples according to all covariates (e.g., sex and education) from control groups to match with treated groups. However, few samples can be exactly matched if there are too many covariates, especially when dealing with continuous covariates (e.g., income). CEM tackles this issue by initially coarsening the continuous covariates into bins (e.g., from income values to high/middle/low level) and subsequently conducting exact matching on the newly binned versions of the covariates. Previous studies demonstrated that CEM should be the first choice if conditions permit, since it surpasses other methods in its capacity to decrease imbalance, model dependence, estimation error, bias, variance, mean square error, and other criteria (Iacus et al., 2012; King & Nielsen, 2019). Another potential method is propensity score matching (PSM), unlike EM or CEM, PSM proposes matching based on one dimension – the probability of receiving the treatment given the observed covariates (Rosenbaum & Rubin, 1983). Despite being a commonly used matching method, PSM may still be susceptible to issues such as increased imbalance, inefficiency, model dependence, and bias (King & Nielsen, 2019).

Considering our dataset with both discrete covariates (e.g., sex) and continuous covariates (e.g., the number of published videos), CEM was used to match similar uploaders from the control group with the treated group. Specifically, 1:1 CEM without replacement was conducted based on six uploader-level covariates: sex, verification, level, VIP, post, and category. A total of 4076 control group uploaders were matched with an adequate balance (see Appendix B), while 64 uploaders in the treatment group did not have similar uploaders in the control group. Finally, our pruned sample includes 8152 uploaders ($N_{treat} = 4{,}076$, $N_{control} = 4076$) with 351,604 videos that were used for within-between modeling.

3.2. Measures

3.2.1. Technological engagement bait

The Bilibili API (http://api.bilibili.com/x/v2/dm/web/view?type=1&oid=) automatically identified the videos with the "triple hits" bar through an "#ATTENTION#" label. Thus, all the videos with the "#ATTENTION#" labels in our sample were coded as technological engagement bait = 1, while other videos were coded as technological engagement bait = 0.

3.2.2. Engagement

Previous studies often measured engagement online through the metrics shown on websites or platforms that reflect the uploader click frequency of certain buttons such as like, retweet, or reply (Linvill et al., 2022; Yi et al., 2022). To fit the context of Bilibili and the "triple hits" bar's function, we measured three indicators of engagement: the number of likes, coins, and favorites.

3.2.3. Control variables

Confounding variables were controlled to make a causal inference about the effect of technological engagement bait. Specifically, user perceptions and behaviors were affected by the source, message, and medium. Considering that technological engagement bait captured medium effects, we controlled source- and message-related variables (see Fig. 1).

Source elements were controlled through uploader attributes. *Sex* was coded as invisible = 0, male = 1, female = 2. *Verification* was coded as unverified uploader = 0, individual-verified uploader = 1, official-verified uploader = 2. *Level* was the activity level of uploaders' accounts obtained from the Bilibili API; *VIP* was coded as normal uploader = 0, VIP uploader = 1. *Post* was measured by the number of videos published by each uploader. *Follower* was measured by the number of followers of each uploader.

Message elements were controlled through video attributes. *High-definition resolution (HD)* reflected the clarity of videos as labeled by Bilibili and was coded as normal video = 0, HD video = 1. *Duration* was measured as the length (seconds) of each video. *Topic* was measured by the video's category, which was assigned by uploaders to indicate the main content and consisted of 15 categories. The descriptive statistics for all the variables were shown in Table 2.

4. Results

4.1. Within-between (WB) models

In our sample, 8152 uploaders published 351,604 videos, which indicated a nested structure (uploader-video) of our data and the assumption of independent observation. A multilevel analysis is required as linear regressions may result in a biased estimation of videos uploaded by the same individual. We applied the within-between (WB) model (Mundlak, 1978) to deal with the nested data and model the contextual effect. This contextual effect was considered a spillover effect: the extent to which applying technological engagement bait to a single video influences engagement with other videos from the same uploader.

In addition, our dependent variables were over-dispersed count variables, which suggested a negative binomial distribution (Coxe et al., 2009). Therefore, we ran a series of WB negative binomial models through the R package *panelr* (Long, 2020). We first ran three intercept-only models to verify the necessity of setting the uploader to a higher level in the multilevel models. The intraclass correlation coefficients (ICC) were 83.6%, 84.3%, and 84.8% respectively for the

Table 2
Descriptive table of variables.

Variables	Descriptive Statistics
Independent Variable	
Technological engagement bait	Bait used: $n = 21546$, 6.1%
	Bait not used: $n = 330058$, 93.9%
Dependent Variables	
Like	$M = 653.94$, $SD = 7880.69$
Coin	$M = 201.38$, $SD = 4616.29$
Favorite	$M = 203.33$, $SD = 3523.94$
Video-level controls	
High-definition resolution	Normal video: $n = 216609$, 61.6%
	HD video: $n = 134995$, 38.4%
Duration	$M = 997.56$, $SD = 7878.79$
Topic	See Appendix C
Uploader-level controls	
Sex	Invisible: $n = 5476$, 67.1%
	Male: $n = 674$, 8.3%
	Female: $n = 2002$, 24.6%
Verification	Unverified uploader: $n = 7862$, 96.4%
	Individual-verified uploader: $n = 244$, 3.0%
	Official-verified uploader: $n = 46$, 0.6%
Level	$M = 4.29$, $SD = 1.29$
VIP	Normal uploader: $n = 5296$, 65.0%
	VIP uploader: $n = 2856$, 35.0%
Post	$M = 43.13$, $SD = 98.67$
Follower	$M = 20598.51$, $SD = 327415.5$

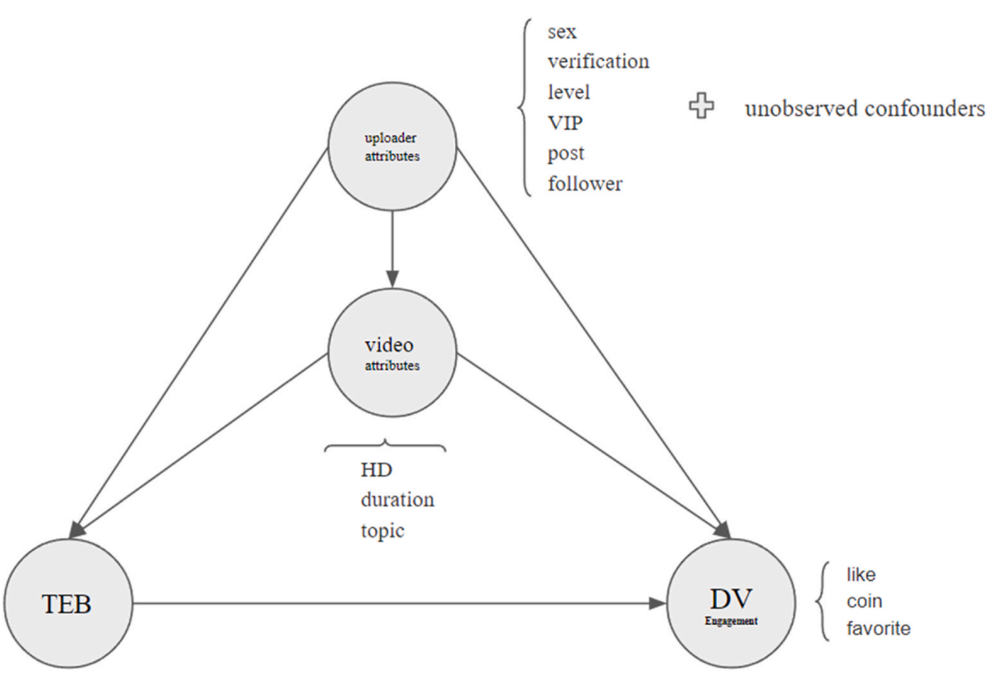


Fig. 1. The Directed Acyclic Graph (DAG) of the Research Design for Causal Inference
Note. Control for the uploader-level and video-level variables can exclude the confounders caused by "source" and "message"; Set "uploader" as the second level in a multilevel model can exclude the uploader-level unobserved confounders. Both help to estimate the real effects of technological engagement bait on engagement. TEB = technological engagement bait; DV = dependent variable (engagement). Difference-in-differences (DID) is another possible design for causal inference, which aims to compare the changes in engagement metrics of each user over time (before and after using TEB) between treated and controlled groups. However, our data reveals that users have the option to use TEB in each video, and they may not consistently use it after their first attempt. Therefore, we cannot identify a specific time point for each user to differentiate between before and after using TEB, making DID unsuitable for this study.

number of likes, coins, and favorites. This result indicates that the uploader level explained the variance of the engagement, thus multilevel models were appropriate.

Before we specify more complicated WB models, we also check whether our model has multicollinearity issues. We ran three multilevel models with all our variables and obtained the variance inflation factor (VIF) through the "check_collinearity" function in R package *performance* (Lüdecke et al., 2021). Since all the VIF values are less than 1.30 (See Appendix D), it can be inferred that there are no multicollinearity issues among these variables (Chatterjee & Hadi, 2015). Finally, three WB models with all the variables were specified.

4.2. Direct and spillover effects of engagement bait

Table 3 summarizes the results of the WB models for like, coin, and favorite, respectively. Full models with control variables are presented in Appendix E. The three baseline models first showed within effects of engagement bait on the number of likes (Model 1: $b = 0.86$, $p < .00$), coins (Model 2: $b = 1.00$, $p < .00$), and favorites (Model 3: $b = 0.88$, $p < .00$). The within part was a fixed-effect model that excluded all the time-invariant video-level confounders and time-varying video-level variables (i.e., HD, duration, and topic) that we controlled for. Based on this, we found a direct causal effect that for any uploader, using technological engagement bait of the "triple hits" bar in a video increased its engagement. Therefore, H1 was supported.

The contextual effects were significant for likes (Model 1: $b = 1.08$, $p < .00$), coins (Model 2: $b = 1.24$, $p < .00$), and favorites (Model 3: $b = 0.80$, $p < .00$). It means that using technological engagement bait in one video had a spillover effect on engagement with other videos from the same uploader. After we blocked the backdoor path through control for uploader and video level variables, the contextual effect of engagement bait remained significant, ruling out the alternative explanation that the effect was caused by other uploader or video attributions. Therefore, H2 was supported.

4.3. Robustness tests

To explore the robustness of estimates obtained from the above baseline models, we additionally specified 12 robustness test models for comparison.

4.3.1. Different matching methods and samples

The datasets obtained through various matching methods are essentially distinct sub-samples derived from the original data. Theoretically, the within and contextual effects of TEB ("Sanlian" bar) should

Table 3
The within and contextual effect of technological engagement bait on engagement with CEM datasets (baseline models).

	Model 1: Like		Model 2: Coin		Model 3: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
Within effect						
TEB	.86***	.01	1.00***	.01	.88***	.02
Contextual effect						
Intercept	3.38***	.14	2.07***	.15	3.11***	.15
imean(TEB)	1.08***	.11	1.24***	.12	.80***	.13
Random effect	*SD*		*SD*		*SD*	
User	1.80		1.60		1.90	
Model fit						
AIC	3092227.55		2000728.27		2222114.27	
BIC	3092712.13		2001212.85		2222598.85	
Pseudo-R^2 (fixed)	.41		.50		.46	
Pseudo-R^2 (total)	.99		.96		.98	

Note. Coefficients of confounders were not shown in the table and can be found in Appendix E. TEB = technological engagement bait. *$p < .05$. **$p < .01$. *$p < .001$.

remain consistent, irrespective of the matching methods employed and the sub-samples obtained. To eliminate the possibility that the effects observed in our baseline models are solely applicable to the specific sample obtained through 1:1 CEM without replacement, we initially rematched a distinct sample using 1:1 PSM without replacement ($N_{treat} =$ 4,140, $N_{control} =$ 4,140, $N_{video} =$ 415,134) to assess the effects of TEB (see matching diagnosis in Appendix F). For cross-validation, we executed three models using the new sample and ensured that the specifications of these models were identical to those of our baseline models. The results in Appendix G showed similar within effects for like (Model 4: $b = 0.90$, $p < .00$), coin (Model 5: $b = 1.02$, $p < .00$), and favorite (Model 6: $b = 0.89$, $p < .00$) and contextual effects for like (Model 4: $b = 1.40$, $p < .00$), coin (Model 5: $b = 1.42$, $p < .00$), and favorite (Model 6: $b = 1.22$, $p < .00$).

Another potential risk associated with estimating the effects of TEB is the relatively limited sample size resulting from 1:1 matching. According to previous studies, K:1 matching can preserve precision by preventing too many control units from being unmatched, but its precision gain diminishes rapidly after 4 (Rosenbaum, 2020), while 1:1 or 1:2 matching generally performs best in terms of mean squared error (Austin, 2010). Therefore, we drew another sample with 2:1 PSM without replacement ($N_{treat} =$ 4,140, $N_{control} =$ 8,280, $N_{video} =$ 569,545), and its matching diagnosis is shown in Appendix H). The results in Appendix I revealed that there were consistent within effects for like (Model 7: $b = 0.90$, $p < .00$), coin (Model 8: $b = 1.03$, $p < .00$), and favorite (Model 9: $b = 0.89$, $p < .00$). Furthermore, there were similar contextual effects for like (Model 7: $b = 1.62$, $p < .00$), coin (Model 8: $b = 1.73$, $p < .00$), and favorite (Model 9: $b = 1.51$, $p < .00$).

From the consistent findings between Models 4–9 and the baseline models, we can partially rule out the influence of different matching methods and samples on the estimation of TEB's effectiveness.

4.3.2. Explanatory and omitted variables tests

The logic of conducting explanatory and omitted variables tests is to ensure that all relevant confounding variables are included, and irrelevant variables are excluded, to maintain the validity of inferences (Neumayer & Plümper, 2017).

In addition to the control variables included in our baseline models, the published time of the video may also have an impact on the number of likes, coins, and favorites it receives. As an illustration, a video published three days ago has been exposed to other users for a longer period compared to a video published just 3 minutes ago. To eliminate this possibility, we incorporated an additional video-level control variable, namely the published time ($M = 503.59$, $SD = 505.56$), into our three baseline models. This variable was measured by calculating the number of days between the video's publication date and the date it was collected for our research. Appendix J shows the results after controlling the published time of videos. Similar within effects were found for like (Model 10: $b = 0.79$, $p < .00$), coin (Model 11: $b = 1.05$, $p < .00$), and favorite (Model 12: $b = 0.95$, $p < .00$). Also, there were similar contextual effects for like (Model 10: $b = 0.98$, $p < .00$), coin (Model 11: $b = 1.58$, $p < .00$), and favorite (Model 12: $b = 1.23$, $p < .00$).

On the other hand, since 67.1% of users' sex is invisible (see Table 2), which may influence the estimation of baseline models, we removed the sex from the uploader-level controls and reran three models for comparison (see Appendix K). We observed similar within effects for like (Model 13: $b = 0.86$, $p < .00$), coin (Model 14: $b = 1.00$, $p < .00$), and favorite (Model 15: $b = 0.88$, $p < .00$), and similar contextual effects for like (Model 13: $b = 1.07$, $p < .00$), coin (Model 14: $b = 1.21$, $p < .00$), and favorite (Model 15: $b = 0.75$, $p < .00$).

Based on the consistent results obtained from Models 10–15 and the baseline models, we can conclude to some extent that the inclusion or exclusion of controls does not significantly impact the estimation of the effectiveness of TEB.

5. Discussion and conclusions

This study introduced the concepts of engagement bait and technological engagement bait and explained them using the cues concept in computer-mediated communication (CMC). We found that technological engagement bait, which contains technological cues, can directly increase user engagement with bait-using videos on Bilibili. Furthermore, this effect spilled over to other videos uploaded by the same user. These findings have important implications for both theoretical and practical aspects of CMC research.

First, this study introduced a general concept of engagement bait to explain a series of similar phenomena in the scope of CMC theories. Compared with clickbait, engagement bait can include baits aiming at any engagement behaviors or metrics, and it is not limited to specific technological features, which can be a powerful theoretical tool for future scholars to examine new baits with emerging techniques. Moreover, following the initiative of previous scholars (Xu & Liao, 2020), this study attempted to use cues as a starting point to understand engagement bait and technological engagement bait. By connecting clickbait studies with established theories in the CMC field, this study provided a theoretical foundation for previously practice-oriented research. Through the lens of cues, we reframed technological engagement bait within the context of media and technology, enabling us to delve into its underlying nature, effectiveness, impact on CMC, and the relationship between humans and technology.

Second, we found a causal effect of technological engagement bait through random sampling, matching, WB modeling, and controlling uploader-level and video-level confounding variables. 12 robustness test models showed consistent results as our baseline models. As Sundar et al.'s (2015) TIME models expected, technological affordances can trigger various heuristics to affect user perceptions and behaviors. Our findings based on observational data further supplemented previous experimental studies (e.g., Guillory & Sundar, 2014; Xu & Sundar, 2014) to increase the generalizability of this argument. More importantly, the real-world setting and the contextual effect in the WB models enabled us to find a spillover effect. The findings indicate that the bait not only increased user engagement with the intended video, but also with other videos from the same creator, regardless of whether those videos employed the bait or not. In line with previous studies (e.g., Bergan et al., 2021; Christandl et al., 2018), this result implies a distensible and long-lasting effect of cues. We provide two possible explanations from the bandwagon (Waddell & Sundar, 2020) and contingency (Lee & Park, 2013) perspectives to explain that individuals' actions are affected by others' actions and their prior actions. The direct and spillover effects of technological engagement bait that we uncovered are of great significance to media and technology scholars, as they address a fundamental question: technology and media not only serve as a channel of transmitting messages between senders and receivers but also have an inherent impact (Sundar et al., 2015). By creating unique technological cues, they can shape people's perceptions and behaviors, and this effect can exist independently of the source and message. However, the specific mechanism of the spillover effect was not examined in this study. We encourage future scholars to investigate the socio-psychological effects of how technological cues form an interaction habit for individuals and an interaction culture in the community.

Several practical implications can be drawn from the current study. Media platforms, particularly those that rely heavily on user-generated content, might need to detect and control engagement bait to prevent low-quality content from receiving an excessive number of interactions and exposure. Contemporary media is a "contestable market" (Munger, 2020, p. 380) where content creators need to compete for the limited attention from the audience. Moreover, the spillover effect we observed signifies a Matthew effect (Rigney, 2010) of the accumulated advantage that more likes and favorites come to the content creators after a bait-using post or video increased their engagement metrics. As a result, bait users may compress the market for high-quality content producers who do not use engagement bait, which is detrimental to media platforms. For example, Facebook has updated a series of algorithms to fight against engagement bait with meaningless content (Silverman & Huang, 2017). However, the various forms of technological engagement bait have been ignored by bait detection and are even encouraged by some platforms, like Bilibili.

It is not surprising that media designers have improved the interactivity of medium technologies, as interaction can enhance user experience and perceptions no matter what triggers it (Sundar et al., 2015). Engagement also positively affects the prospective activity and output quality of content creators (Cheng et al., 2014). From this perspective, it may not be the best course of action to ban all engagement bait. Perhaps platforms can consider using similarity algorithms instead of popularity rankings to recommend content to fight engagement bait. TikTok is one platform that already uses this strategy. Regarding content creators, although the findings of this study supported the positive effect of using bait to increase engagement, overusing bait may trigger an intrusiveness heuristic (Diao & Sundar, 2004) and lower the perceived quality of the content (Molyneux & Coddington, 2020). Given its spillover effect, content producers should utilize engagement bait in moderation to strike a balance between not disrupting user experience and gaining higher engagement.

5.1. Limitations and future directions

Several limitations of the current study need to be noted. First, the causal inference might be biased as a result of unobserved confounding variables. For example, we only controlled some related variables (i.e., image quality, duration, and topic) but did not directly control video content and quality because of the difficulty to measure it. Although the descriptive text content could be controlled by state-of-the-art methods like double machine learning, how to accurately control video quality or content is an unsettled issue for future scholars. One other concern pertains to the time frame during which we collected the number of likes, coins, and favorites. Bilibili API only provides the total number of engagement metrics of each video. Thus, we are unable to know which engagements took place before the "triple hits" button was displayed and which took place afterwards. This may also influence the estimation of the effects of technological engagement bait.

Third, although the findings of this study provide empirical evidence about the effectiveness of engagement bait, its underlying mechanism was unexplored. Scholars can evaluate the possible explanations we provided and summarize the different heuristics cued by engagement bait. Notably, the use of heuristics is not equal to or limited to heuristic processing, meaning that heuristics can be involved in systematic processing as an analytical tool (Sundar, 2008). Therefore, systematic processing should be taken into account when studying the psychological mechanism that underlies engagement bait.

Finally, our results only assessed the effects of bait on engagement behaviors. According to the TIME models (Sundar et al., 2015), technological cues have power in persuasion and affect various user perceptions and other behaviors. Studies of clickbait have also found that it lowers the audience's perceived quality and credibility regarding bait-using content (Molyneux & Coddington, 2020). Thus, more outcomes must be examined in future engagement bait studies to fully comprehend its effectiveness.

Despite these limitations, this study offered an explication of engagement bait that will help to practically detect it in digital media and comprehend its theoretical effects. Furthermore, we empirically demonstrated how technological engagement bait based on technological cues influences users' behaviors in a real-world setting in both direct and spillover ways. The findings elucidated that media technologies participate in human socialization and the creation of new types of cues rather than merely transforming information and reproducing social reality. This study advances our understanding of engagement bait and the human-technology relationship in the context of CMC.

Credit author statement

Wanjiang Jacob Zhang: Conceptualization, Methodology, Formal analysis, Validation, Writing – original draft, Visualization. **Jingjing Yi**: Conceptualization, Writing – original draft, Writing – review & editing, Visualization, Data curation. **Hai Liang**: Methodology, Writing – review & editing, Supervision, Project administration.

Endnote

1. Bilibili is the largest video-sharing platform in China. It is similar to YouTube. It was founded to share content related to ACG (anime, comics, and games) and has evolved into a full-spectrum video community with user-generated content (UGC) that covers a wide array of interests, including lifestyle, entertainment, technology, knowledge, and so on. Bilibili is popular among Chinese youth and had 271.7 million average monthly active users (MAUs) and 72.2 million average daily active users (DAUs) as of 2021 (Bilibili, 2022).
2. Bullet chat, or “danmu” in Chinese and “danmaku” in Japanese, is a form of scrolling text posted by viewers to interact with other viewers while watching a video on Bilibili. The “triple hits” bar is a kind of bullet chat update by Bilibili. It is posted by video uploaders rather than other viewers, and viewers can interact with the bar by clicking buttons on it.
3. Like, favorite, and drop-coin are the main ways for the audience to interact with videos on Bilibili. Clicking like simply indicates that a viewer enjoyed a particular video. Clicking favorite bookmarks the video for future viewing. The coin is the limited free virtual currency provided by Bilibili. Viewers can select to drop zero, one, or two coins for each video. Bilibili gives monetary rewards to video uploaders based on the coins they collect.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

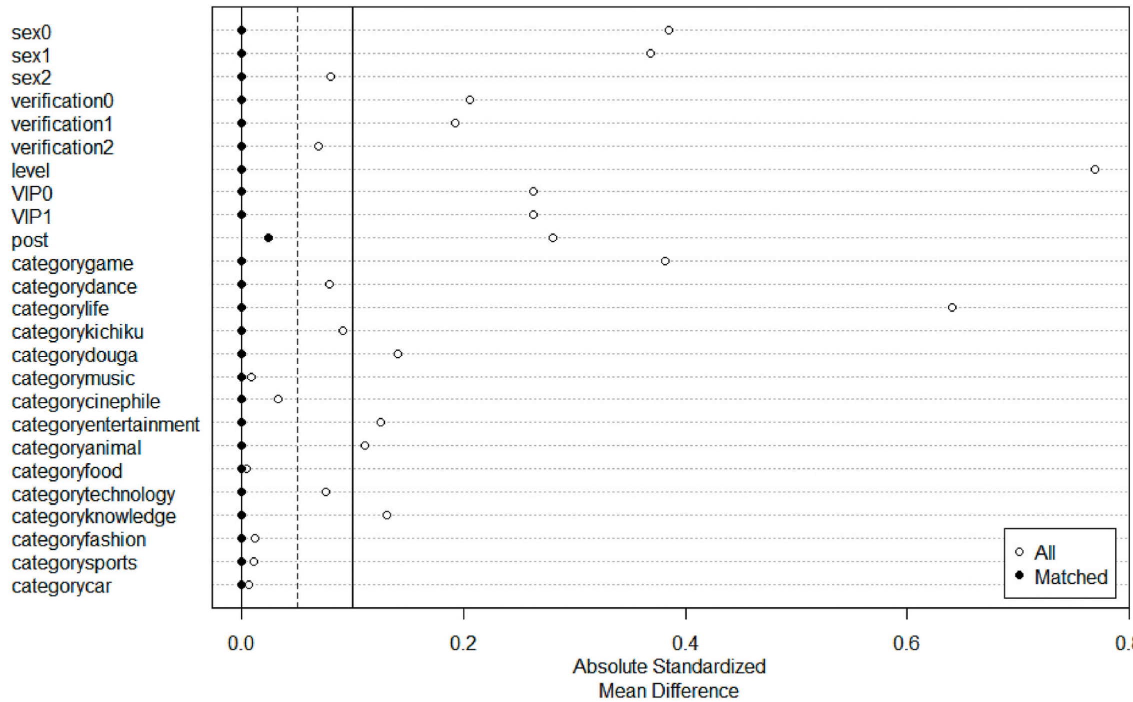
Appendix A

A Sample “Triple Hits” Bar in a Video

Note. The red box area shows the “triple hits” bar. Both web and mobile versions of Bilibili support this function.

Appendix B

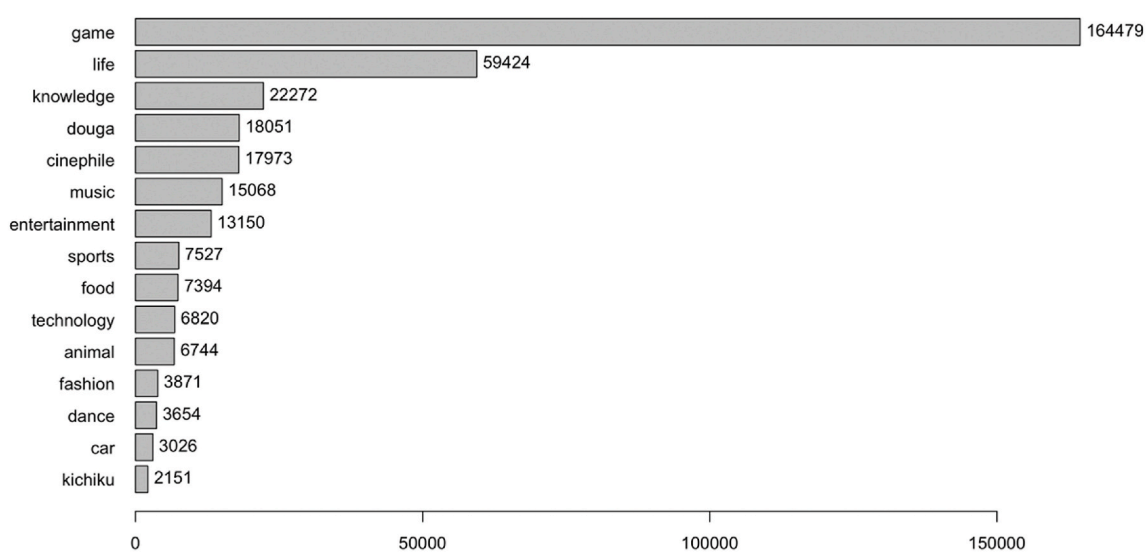
The Diagnosis of CEM Quality Indicated by Absolute Standardized Mean Difference with CEM Dataset



Note. The white point means the degree of balance of the covariate distributions before matching indicated by absolute standardized mean difference, while the black color means the degree of balance of the covariate distributions after matching. The closer the point is close to 0, the more balanced the matching result we get. Because we used coarsened exact matching (CEM), all the categorical covariates could match exactly, thus their absolute standardized mean difference is equal to zero. The balance improved for the continuous covariable (post) as the absolute standardized mean difference decreased under 0.2, which is an acceptable value (Rubin, 2001).

Appendix C

The Frequency of the Control Variable "Topic"



Appendix D

VIF and Tolerance for Checking Multicollinearity

Variables	Model 1: Like		Model 2: Coin		Model 3: Favorite	
	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance
TEB	1.00	1.00	1.00	1.00	1.00	1.00
HD	1.00	1.00	1.00	1.00	1.00	1.00
Duration	1.00	1.00	1.00	1.00	1.00	1.00
Topic	1.02	.98	1.02	.98	1.02	.98
Sex	1.05	.96	1.05	.96	1.05	.96
Official Type	1.24	.81	1.23	.81	1.23	.81
Follower	1.20	.84	1.19	.84	1.19	.84
Level	1.29	.77	1.28	.78	1.29	.78
VIP	1.23	.81	1.23	.82	1.23	.81
Post	1.03	.97	1.03	.97	1.03	.97

Appendix E

The Within and Contextual Effect of Technological Engagement Bait (TEB) on Engagement with the Datasets Obtained by 1:1 CEM without Replacement (Baseline Models)

	Model 1: Like		Model 2: Coin		Model 3: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
Within effect						
TEB	.86***	.01	1.00***	.01	.88***	.02
Video-level controls						
Duration	.07***	.00	.16***	.00	.21***	.00
HD	.02***	.01	−.01	.01	−.08***	.01
Topic_douga	.36***	.02	.23***	.03	.40***	.03
Topic_life	−.54***	.02	−.64***	.02	−.86***	.03
Topic_game	−.72***	.02	−.98***	.02	−1.40***	.03
Topic_dance	.14***	.04	−.01	.05	.54***	.06
Topic_kichiku	.37***	.04	.49***	.05	.18***	.06
Topic_sports	.00	.03	−.19***	.04	−.13***	.04
Topic_knowledge	−.16***	.03	−.22***	.03	.01	.03
Topic_cinephile	−.14***	.02	−.32***	.03	−.25***	.03
Topic_entertainment	.31***	.03	−.03	.03	.35***	.03
Topic_animal	−.4***	.03	−.70***	.04	−.98***	.04
Topic_technology	.05	.03	−.22***	.04	−.21***	.04
Topic_car	.35***	.05	.07	.06	.26***	.06
Topic_food	−.74***	.03	−.68***	.04	−.88***	.05
Topic_fashion	−.31***	.04	−.51***	.05	−.22***	.06
Contextual effect						
Intercept	3.38***	.14	2.07***	.15	3.11***	.15
imean(TEB)	1.08***	.11	1.24***	.12	.80***	.13
Video-level controls						
imean(duration)	−.06	.04	−.03	.06	.05	.04
imean(HD)	.34***	.07	.21***	.06	.01	.07
imean(topic_douga)	.67***	.16	.33*	.15	.25	.18
imean(topic_life)	−.56***	.14	−.97***	.13	−1.28***	.15
imean(topic_game)	−.24	.13	−.37***	.12	−.91***	.14
imean(topic_dance)	.25	.23	.42*	.22	−.07	.25
imean(topic_kichiku)	1.31***	.29	1.22***	.27	1.06***	.31
imean(topic_sports)	−.02	.25	−.29	.23	−.25	.27
imean(topic_knowledge)	.13	.16	.12	.15	.26	.17
imean(topic_cinephile)	.77***	.18	.28	.17	.43*	.19
imean(topic_entertainment)	.73***	.21	−.10	.20	.60**	.23
imean(topic_animal)	−.63*	.27	−1.23***	.25	−1.56***	.29
imean(topic_technology)	.21	.24	.16	.22	.37	.25
imean(topic_car)	−.15	.37	−.50	.34	−.81*	.40
imean(topic_food)	.22	.26	−.06	.24	−.41	.28
imean(topic_fashion)	1.00***	.31	.69*	.29	.96	.34
Uploader-level controls						
Follower	.15***	.02	.14***	.02	.12	.02
Level	.76***	.02	1.01***	.02	.96***	.02
Post	.48***	.11	−.30***	.09	.11	.11
Male	.13**	.05	.12**	.05	.12*	.06
Female	.25***	.08	.27***	.08	.28***	.09
Individual-verified	3.48***	.16	3.51***	.14	3.16***	.17
Official-verified	1.98***	.31	2.10***	.28	1.79***	.33
VIP	.06	.05	−.04	.05	.04	.05
Random effect	*SD*		*SD*		*SD*	
User	1.80		1.60		1.90	

(*continued on next page*)

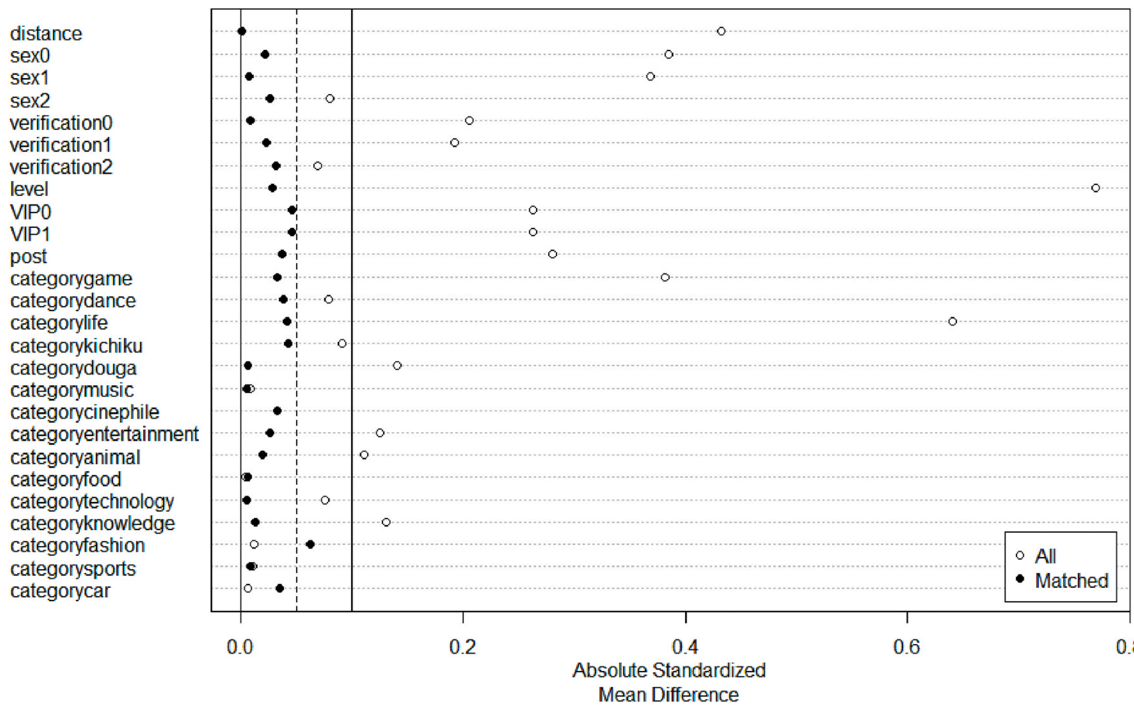
(*continued*)

Random effect	*SD*	*SD*	*SD*
Model fit			
AIC	3092227.55	2000728.27	2222114.27
BIC	3092712.13	2001212.85	2222598.85
Pseudo-R^2 (fixed)	.41	.50	.46
Pseudo-R^2 (total)	.99	.96	.98

Note. *$p < .05$. **$p < .01$. ***$p < .001$.

Appendix F

The Diagnosis of PSM Quality Indicated by Absolute Standardized Mean Difference with the Datasets Obtained by 1:1 PSM without Replacement



Appendix G

The Within and Contextual Effect of Technological Engagement Bait (TEB) on Engagement with the Datasets Obtained by 1:1 PSM without Replacement

	Model 4: Like		Model 5: Coin		Model 6: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
Within effect						
TEB	.90***	.01	1.02***	.01	.89***	.02
Video-level controls						
Duration	.09***	.00	.14***	.00	.18***	.00
HD	.00	.01	.11***	.01	−.06***	.01
Topic_life	−.50***	.02	−.49***	.03	−.58***	.03
Topic_game	−.68***	.02	−.93***	.03	−1.16***	.03
Topic_knowledge	−.49***	.03	−.26***	.03	−.12***	.03
Topic_douga	.37***	.02	.31***	.03	.57***	.03
Topic_kichiku	.59***	.05	.59***	.06	.46***	.06
Topic_cinephile	−.04	.02	.13***	.03	.09**	.03
Topic_technology	−.33***	.03	−.49***	.04	−.22***	.04
Topic_dance	−.36***	.03	−.33***	.05	.29***	.05
Topic_sports	−.20***	.03	−.35***	.04	.22***	.04
Topic_entertainment	−.23**	.02	−1.24***	.03	−.10***	.03
Topic_animal	−.44***	.03	−.81***	.04	−.86***	.04
Topic_car	.27***	.05	.21***	.06	.45***	.06
Topic_food	−.69***	.03	−.77***	.04	−.78***	.04

(*continued on next page*)

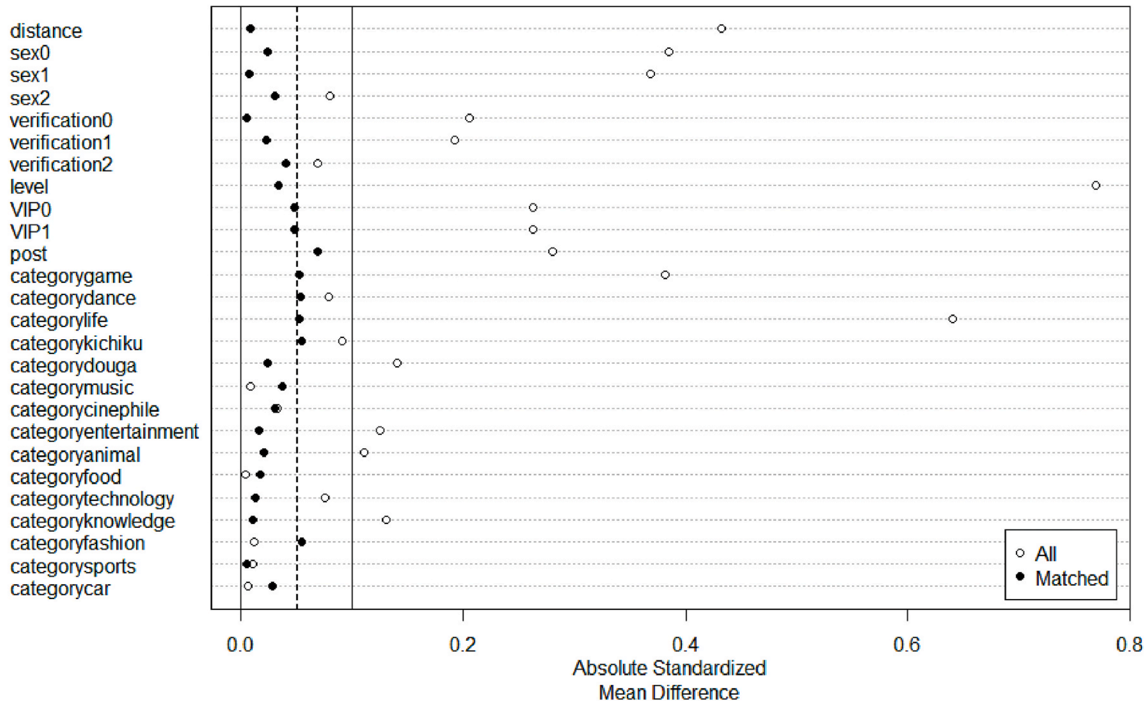
(*continued*)

	Model 4: Like		Model 5: Coin		Model 6: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
Topic_fashion	−.49***	.03	−.38***	.05	.15***	.05
Contextual effect						
Intercept	3.16***	.15	1.54***	.22	2.50***	.22
imean(TEB)	1.40***	.11	1.42***	.17	1.22***	.16
Video-level controls						
imean(duration)	−.05	.05	.04	.07	.14*	.06
imean(HD)	.35***	.07	.15	.10	.02	.10
imean(topic_life)	−.65***	.14	−1.13***	.21	−1.43***	.21
imean(topic_game)	−.17	.13	−.39*	.19	−.86***	.19
imean(topic_knowledge)	.50***	.16	.13	.24	.66***	.23
imean(topic_douga)	.75***	.16	.24	.24	.36	.24
imean(topic_kichiku)	.91***	.28	.79*	.41	.75	.41
imean(topic_cinephile)	.67***	.18	−.13	.26	.45	.26
imean(topic_technology)	.78***	.23	.67*	.34	.79*	.34
imean(topic_dance)	.92***	.22	.89***	.31	.57	.31
imean(topic_sports)	.26	.25	−.23	.37	−.53	.36
imean(topic_entertainment)	1.53***	.21	1.39***	.31	1.66***	.30
imean(topic_animal)	−.57*	.27	−.99**	.40	−1.52***	.39
imean(topic_car)	−.45	.33	−1.06*	.48	−1.31**	.48
imean(topic_food)	.24	.26	−.03	.38	−.21	.38
imean(topic_fashion)	1.03***	.27	.32	.40	.44	.40
Uploader-level controls						
Follower	.19***	.02	.24***	.03	.16***	.03
Level	.83***	.02	1.18***	.04	1.04***	.04
Post	.45***	.13	−.48**	.19	.09	.18
Male	.09	.05	.16*	.08	.18*	.07
Female	.34***	.08	.35***	.12	.41***	.12
Individual-verified	3.38***	.15	3.29***	.21	3.10***	.21
Official-verified	1.51***	.26	1.28***	.39	1.44***	.38
VIP	.07	.05	.02	.07	−.00	.07
Random effect	*SD*		*SD*		*SD*	
User	1.79		2.63		2.58	
Model fit						
AIC	3614274.72		2197241.97		2543790.31	
BIC	3614766.78		2197734.03		2544282.37	
Pseudo-R^2 (fixed)	.47		.39		.52	
Pseudo-R^2 (total)	.99		.98		.98	

Note. *$p < .05$. **$p < .01$. ***$p < .001$.

Appendix H

The Diagnosis of PSM Quality Indicated by Absolute Standardized Mean Difference with the Datasets Obtained by 2:1 PSM without Replacement



Appendix I

The Within and Contextual Effect of Technological Engagement Bait (TEB) on Engagement with the Datasets Obtained by 2:1 PSM without Replacement

	Model 7: Like		Model 8: Coin		Model 9: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
Within effect						
TEB	.90***	.01	1.03***	.01	.89***	.02
Video-level controls						
Duration	.08***	.00	.15***	.00	.19***	.00
HD	.05***	.01	.10***	.01	−.03***	.01
Topic_douga	.47***	.02	.41***	.02	.62***	.03
Topic_life	−.37***	.02	−.37***	.02	−.47***	.02
Topic_knowledge	−.31***	.02	−.35***	.03	.06*	.03
Topic_sports	−.10***	.03	−.18***	.03	.23***	.04
Topic_cinephile	−.01	.02	−.02	.03	.14***	.03
Topic_entertainment	−.15***	.02	−.61***	.03	−.17***	.03
Topic_game	−.56***	.02	−.8***	.02	−1.05***	.02
Topic_animal	−.23***	.03	−.54***	.03	−.61***	.04
Topic_kichiku	.74***	.04	.81***	.05	.62***	.05
Topic_technology	−.18***	.03	−.50***	.03	−.06	.03
Topic_dance	−.13***	.03	−.06	.04	.45***	.04
Topic_car	.38***	.04	.26***	.05	.51***	.06
Topic_food	−.49***	.03	−.56***	.03	−.53***	.04
Topic_fashion	−.54***	.03	−.32***	.04	.07	.04
Contextual effect						
Intercept	2.98***	.12	1.40***	.11	2.37***	.13
imean(TEB)	1.62***	.11	1.73***	.10	1.51***	.11
Video-level controls						
imean(duration)	−.03	.04	.04	.04	.15***	.04
imean(HD)	.39***	.06	.18***	.05	.04	.06
imean(topic_douga)	.67***	.13	.30**	.12	.52***	.14
imean(topic_life)	−.82***	.11	−1.24***	.11	−1.50***	.12
imean(topic_knowledge)	.21	.13	.21	.12	.39**	.14
imean(topic_sports)	.04	.2	−.41*	.19	−.43*	.21
imean(topic_cinephile)	.62***	.14	−.09	.13	.32*	.15
imean(topic_entertainment)	1.40***	.17	.75***	.16	1.69***	.18
imean(topic_game)	−.26**	.1	−.45***	.1	−.91***	.11

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(*continued*)

	Model 7: Like		Model 8: Coin		Model 9: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
imean(topic_animal)	−.97***	.22	−1.61***	.20	−1.90***	.23
imean(topic_kichiku)	.88***	.23	.94***	.21	1.01***	.25
imean(topic_technology)	.39*	.19	.47**	.17	.43*	.20
imean(topic_dance)	.54***	.18	.49***	.16	.30	.19
imean(topic_car)	−.57*	.27	−1.25***	.26	−1.31***	.29
imean(topic_food)	.10	.21	−.02	.19	−.32	.22
imean(topic_fashion)	.83***	.22	.16	.20	.37	.23
Uploader-level controls						
Follower	.17***	.02	.18***	.02	.15***	.02
Level	.80***	.02	1.11***	.02	1.02***	.02
Post	.43***	.11	−.53***	.09	.13	.11
Female	.30***	.07	.38***	.06	.39***	.07
Male	.10**	.04	.13***	.04	.10*	.04
Individual-verified	3.59***	.12	3.51***	.11	3.17***	.13
Official-verified	1.40***	.21	1.39***	.19	1.49***	.22
VIP	.08*	.04	−.00	.04	.06	.04
Random effect	*SD*		*SD*		*SD*	
User	1.77		1.56		1.82	
Model fit						
AIC	4798614.48		2903384.32		3458396.62	
BIC	4799120.75		2903890.56		3458902.89	
Pseudo-R^2 (fixed)	.47		.60		.52	
Pseudo-R^2 (total)	.99		.98		.98	

Note. *$p < .05$. **$p < .01$. ***$p < .001$.

Appendix J

The Within and Contextual Effect of Technological Engagement Bait (TEB) on Engagement with CEM Baseline Models Adding a Control Variable Published Time

	Model 10: Like		Model 11: Coin		Model 12: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
Within effect						
TEB	.79***	.01	1.05***	.01	.95***	.02
Video-level controls						
Duration	.08***	.00	.15***	.00	.20***	.00
Pub Time	−.26***	.00	.16***	.00	.26***	.01
HD	.00	.01	.01	.01	−.05***	.01
Topic_douga	.39***	.02	.22***	.03	.37***	.03
Topic_life	−.55***	.02	−.62***	.02	−.86***	.03
Topic_game	−.74***	.02	−.97***	.02	−1.40***	.03
Topic_dance	.15***	.04	−.02	.05	.5***	.06
Topic_kichiku	.36***	.04	.48***	.05	.14**	.06
Topic_sports	.01	.03	−.19***	.04	−.13***	.04
Topic_knowledge	−.18***	.02	−.19***	.03	.03	.03
Topic_cinephile	−.14***	.02	−.31***	.03	−.26***	.03
Topic_entertainment	.32***	.03	−.03	.03	.32***	.03
Topic_animal	−.44***	.03	−.67***	.04	−.95***	.04
Topic_technology	.00	.03	−.18***	.04	−.15***	.04
Topic_car	.3***	.05	.10	.06	.29***	.06
Topic_food	−.75***	.03	−.67***	.04	−.86***	.05
Topic_fashion	−.3***	.04	−.51***	.05	−.24***	.06
Contextual effect						
Intercept	3.45***	.14	1.89***	.13	2.90***	.15
imean(TEB)	.98***	.12	1.58***	.12	1.23***	.13
Video-level controls						
imean(duration)	−.07	.04	−.03	.04	.05	.04
imean(published time)	.10***	.03	.21***	.03	.20***	.03
imean(HD)	.31***	.07	.32***	.07	.13	.08
imean(topic_douga)	.62***	.16	.36*	.16	.29	.18
imean(topic_life)	−.63***	.14	−.83***	.14	−1.10***	.15
imean(topic_game)	−.28*	.13	−.25*	.12	−.76***	.14
imean(topic_dance)	.20	.23	.46*	.22	−.01	.25
imean(topic_kichiku)	1.28***	.29	1.23***	.28	1.09***	.32
imean(topic_sports)	−.07	.25	−.20	.24	−.15	.27
imean(topic_knowledge)	.10	.16	.21	.16	.37*	.18
imean(topic_cinephile)	.76***	.18	.28	.17	.43*	.20
imean(topic_entertainment)	.72***	.21	−.09	.20	.60**	.23
imean(topic_animal)	−.63*	.27	−1.13***	.26	−1.45***	.30

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(*continued*)

	Model 10: Like		Model 11: Coin		Model 12: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
imean(topic_technology)	.22	.23	.22	.23	.43	.26
imean(topic_car)	−.17	.37	−.38	.35	−.67	.40
imean(topic_food)	.20	.26	−.04	.25	−.40	.29
imean(topic_fashion)	.95***	.31	.69*	.30	.96***	.34
Uploader-level controls						
Follower	.15***	.02	.15***	.02	.13***	.02
Level	.79***	.02	.93***	.02	.85***	.03
Post	.46***	.10	−.26**	.10	.13	.11
Male	.12*	.05	.15***	.05	.16**	.06
Female	.25***	.08	.29***	.08	.29***	.09
Individual-verified	3.47***	.16	3.51***	.15	3.17***	.17
Official-verified	2.00***	.31	2.05***	.29	1.72***	.33
VIP	.07	.05	−.06	.05	.02	.05
Random effect	*SD*		*SD*		*SD*	
User	1.78		1.68		1.92	
Model fit						
AIC	3088668.87		2000511.18		2220189.01	
BIC	3089175.00		2001017.30		2220695.13	
Pseudo-R^2 (fixed)	.42		.49		.47	
Pseudo-R^2 (total)	.99		.97		.98	

Note. *$p < .05$. **$p < .01$. ***$p < .001$.

Appendix K

The Within and Contextual Effect of Technological Engagement Bait (TEB) on Engagement with CEM Baseline Models Deleting a Control Variable Sex

	Model 13: Like		Model 14: Coin		Model 15: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
Within effect						
TEB	.86***	.01	1.00***	.01	.88***	.02
Video-level controls						
Duration	.07***	.00	.16***	.00	.21***	.00
HD	.02***	.01	−.00	.01	−.08***	.01
Topic_douga	.36***	.02	.23***	.03	.40***	.03
Topic_life	−.54***	.02	−.64***	.02	−.86***	.03
Topic_game	−.72***	.02	−.98***	.02	−1.41***	.03
Topic_dance	.14***	.04	−.01	.05	.54***	.06
Topic_kichiku	.37***	.04	.49***	.05	.18***	.06
Topic_sports	.00	.03	−.19***	.04	−.13***	.04
Topic_knowledge	−.16***	.03	−.22***	.03	.01	.03
Topic_cinephile	−.14***	.02	−.32***	.03	−.25***	.03
Topic_entertainment	.31***	.03	−.03	.03	.35***	.03
Topic_animal	−.40***	.03	−.70***	.04	−.99***	.04
Topic_technology	.05	.03	−.22***	.04	−.21***	.04
Topic_car	.35***	.05	.07	.06	.27***	.06
Topic_food	−.75***	.03	−.68***	.04	−.88***	.05
Topic_fashion	−.31***	.04	−.51***	.05	−.22***	.06
Contextual effect						
Intercept	3.44***	.14	2.13***	.13	3.19***	.16
imean(TEB)	1.07***	.11	1.21***	.11	.75***	.13
Video-level controls						
imean(duration)	−.06	.04	−.02	.04	.06	.05
imean(HD)	.34***	.07	.21***	.07	.01	.08
imean(topic_douga)	.68***	.16	.33*	.16	.23	.19
imean(topic_life)	−.56***	.14	−.97***	.14	−1.31***	.16
imean(topic_game)	−.26*	.13	−.39***	.12	−.95***	.15
imean(topic_dance)	.35	.23	.54*	.22	.02	.26
imean(topic_kichiku)	1.29***	.29	1.19***	.28	1.01***	.33
imean(topic_sports)	−.03	.25	−.30	.24	−.29	.29
imean(topic_knowledge)	.12	.16	.12	.16	.24	.19
imean(topic_cinephile)	.76***	.18	.26	.17	.39	.21
imean(topic_entertainment)	.74***	.21	−.08	.21	.59*	.24
imean(topic_animal)	−.65*	.27	−1.24***	.26	−1.60***	.31
imean(topic_technology)	.18	.24	.13	.23	.32	.27
imean(topic_car)	−.17	.37	−.51	.36	−.86*	.42
imean(topic_food)	.22	.26	−.05	.25	−.41	.30
imean(topic_fashion)	1.04***	.31	.74**	.30	.97**	.36
Uploader-level controls						

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(*continued*)

	Model 13: Like		Model 14: Coin		Model 15: Favorite	
	b	*(SE)*	*b*	*(SE)*	*b*	*(SE)*
Follower	.15***	.02	.14***	.02	.13***	.02
Level	.77***	.02	1.02***	.02	.97***	.03
Post	.47***	.11	−.29***	.10	.12	.12
Individual-verified	3.48***	.16	3.51***	.15	3.16***	.18
Official-verified	1.93***	.31	2.06***	.29	1.74***	.35
VIP	.05	.05	−.05	.05	.04	.06
Random effect	*SD*		*SD*		*SD*	
User	1.80		1.69		2.04	
Model fit						
AIC	3092248.59		2001225.48		2222323.55	
BIC	3092711.64		2001688.53		2222786.60	
Pseudo-R^2 (fixed)	.41		.47		.42	
Pseudo-R^2 (total)	.99		.96		.98	

Note. *$p < .05$. **$p < .01$. ***$p < .001$.

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