Impacts of Hiding Friends' Liked Content on User-Content Engagement across Newsfeed Channels

Xiaohui Zhang
Arizona Sate University, xiaohuizhang@asu.edu

Qinglai He
University of Wisconsin - Madison, qinglai.he@wisc.edu

Zhongju Zhang
Arizona State University, zhongju.zhang@asu.edu

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Xiaohui Zhang
Arizona State University
Tempe, AZ, USA
XiaohuiZhang@asu.edu

Qinglai He
University of Wisconsin - Madison
Madison, WI, USA
qinglai.he@wisc.edu

Zhongju (John) Zhang
Arizona State University
Tempe, AZ, USA
zhongju.zhang@asu.edu

Abstract

Social media platforms often distribute content through different newsfeed channels, most commonly, social networks, algorithmic recommendations and trending content. Prior literature has investigated each channel's impact on user-content engagement. However, little is known about the relationships between these channels. We investigate the impacts of limiting content display from the social network channel on the quantity and diversity of user-engaged content across channels. We leverage a natural experiment, where a social media platform hides friends' liked content from the social network channel, to identify the impacts. Results show that hiding friends' liked content reduces the quantity of users' content engagement on the entire platform. Across channels, users increase their engagement with trending content but decrease their engagement with algorithmic recommendations. Further, restricting exposure to friends' liked content reduces the diversity of users' content engagement. Our results highlight the intercorrelation of user-content engagement across newsfeed channels and provide insights for newsfeed designs.

Keywords: Social media, Newsfeed Channel, User-content Engagement, Social network, Algorithmic recommendation, Trending content

Introduction

Social media has become an integral part of our daily life. We use social media to share information, interact with others, and communicate thoughts. On almost all types of social media platforms, there is likely a basic yet powerful feature of *Likes/Voteups* that allows platform users to easily signal their approval/agreement of online content. These likes/voteups represent users' engagements with the content, i.e., user-content engagement; they indicate users' active consumption, interaction, and attention toward the content (Burtch et al., 2022). User-content engagement records generate a rich stream of data, which can yield valuable insights when analyzed (Wu et al., 2015). In fact, platform owners and companies have been sifting through the vast amounts of Likes data in order to provide customers with personalized and better experiences. Hence, it is important to understand user-content engagement patterns on social media platforms.

With the evolution of data-analytics techniques, social media platforms gradually go beyond social networks. Alongside content from users' social networks, algorithmic recommended content and trending content are widely utilized to curate users' newsfeeds (Yang & Peng, 2020). For instance, Twitter personalizes each user's newsfeed by aggregating content from three major sources: friend tweeted and liked posts, trending content, and algorithmic recommendations (i.e., you might like). We illustrate the three typical newsfeed channels utilized by dominant social media platforms in Figure 1. These three newsfeed channels engage users through distinct mechanisms. Researchers have investigated each channel's independent influence on people's content engagement. The social network channel displays user-driven content (user-posted or -liked content) and delivers such content via user self-formed networks. It affects user-content engagement primarily through interpersonal influence (Tang et al., 2019). The trending channel presents content based on the real-time content popularity on the whole platform. It induces user-content engagement through the popularity influence (Dewan et al., 2017). The algorithmic recommendation channel is primarily designed and controlled by platform algorithms. It motivates user-content engagement by serving content that matches user preferences and platforms' business interests (Lambrecht et al., 2021).

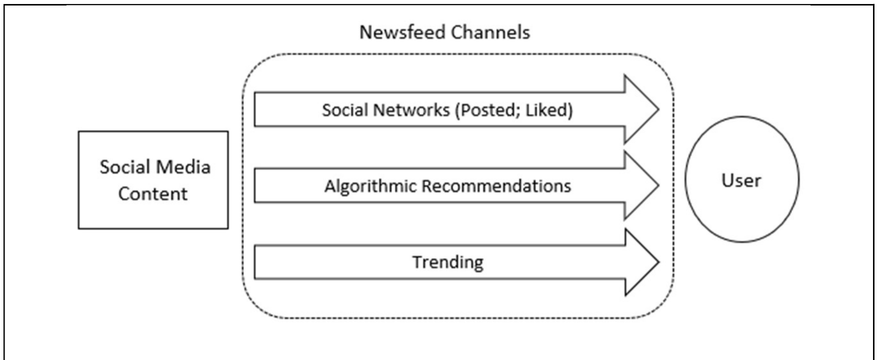

Figure 1. Illustration of Newsfeed Channels

Nowadays, the above three newsfeed channels are rarely isolated from each other. Most social media platforms utilize multiple newsfeed channels simultaneously. In the newsfeed curation process, platforms may intentionally promote/hide certain newsfeed channels depending on their strategic positioning and operation goals. For instances, TikTok identifies itself as an entertainment platform and therefore prioritizes algorithmic recommendations to retain users; LinkedIn digs deep in the professional career context and relies on social networks to foster interpersonal relationships. However, promoting/hiding content in a specific channel likely leads to changes in user-content engagement patterns on the entire platform as well as across channels. To the best of our knowledge, little is known about that relationship between newsfeed channels. It is unclear whether the three newsfeed channels complement users' content demand or compete for users' limited attention. Without a clear understanding of such relationships, the actions taken by the platform owner to promote or hide certain content can annoy users and in some cases backfire. For example, the recent "Make Instagram Instagram again" campaign reflects users' negative reactions toward Instagram's newsfeed changes which downplay content on social networks and promote algorithmic recommendations.[1]

The above knowledge gaps and realistic tensions motivate us to examine how hiding content in the social network channel influences users' engagement with content in the other two channels. Specifically, we focus on friends' liked content, an important component of the social network channel. Seeing what friends liked is a critical information diffusion mechanism of social media, and such content constitutes a large proportion of users' timelines (Mattke et al., 2020).

Hiding friends' liked content may have mixed impacts on people's content engagement patterns (Agarwal et al., 2021; Tang et al., 2019). On the one hand, all newsfeed channels compete for users' limited attention

[1] Source: https://www.wsj.com/articles/make-instagram-instagram-again-the-apps-evolution-is-causing-users-to-question-its-future-11658921581 (Last accessed: August 22, 2022)

(Filippas & Horton, 2021). With less content from one channel, users may shift their attention and engage with content from other newsfeed channels. On the other hand, users have different goals in their content engagement (Park et al., 2009) and each newsfeed channel has its unique IT affordances that can satisfy people's different needs (Karahanna et al., 2018). If hiding friends' liked content hurt the platform's affordances, people may reduce their content engagement in certain channels. Additionally, hiding friends' liked content might further influence the diversity of user-engaged content (Bakshy et al., 2015). Given the above research gaps and mixed consequences of hiding friends' liked content, we seek to address the following research questions in this study:

> *RQ1: How does hiding friends' liked content affect the quantity of user-engaged content on the entire platform and across newsfeed channels?*

> *RQ2: How does hiding the supply of friends' liked content affect the diversity of user-engaged content?*

Hiding friends' liked content would lead to users' attention re-allocation and subsequent content engagement across channels. Therefore, we capitalize on the selective attention theory to theoretically analyze the questions. The selective attention theory describes how humans allocate limited attention to different objects based on the individual's expertise, goal-directedness, and environmental cues (Moore & Zirnsak, 2017). This theory provides us with a theoretical framework to develop hypotheses on users' subsequent content engagement across different newsfeed channels.

To empirically answer the research questions, we collect and analyze data from a large social media platform in Asia. The platform simultaneously utilizes the three discussed channels, social networks, algorithmic recommendations, and trending content to curate users' newsfeeds. In December 2020, this platform announced a policy change to hide friends' liked content from the newsfeed to promote more original user-created content. Although users can still access friends' liked content from a hidden secondary page, this change significantly reduces the quantity and visibility of social network-driven content on the newsfeed. We take advantage of this exogenous shock to conduct this study. It is worth noting that our focal platform only changed its newsfeed curation on mobile applications but not on their desktop website. Thus, the mobile and web applications form an ideal natural experiment setting for our study. We identify treatment and control users from these two types of applications and conduct a series of Difference-in-Differences (DiD) analyses to examine the impact of friends' liked content on users' subsequent content engagement.

The analyses offer several interesting findings. First, we find that hiding friends' liked content significantly reduces the quantity of user-engaged content on the entire platform, especially in the long run. Among three newsfeed channels, users increase their engagement in trending content but decrease their engagement in the algorithmic recommendation channel. Regarding content diversity, we find that reducing exposure to friends' liked content leads users to engage with less diverse content. Moreover, our results also reveal the heterogeneous effects based on users' social orientation and tenure. Social-oriented users exhibit a larger drop in engagement quantity and diversity. These users also show more aversion toward algorithmic recommended content but a stronger preference toward trending content. Conversely, we find that users with longer tenure are less likely to be affected by newsfeed change. These users exhibit a smaller engagement decrease and are more receptive to algorithmic recommended content.

Our research makes several theoretical and practical contributions. Theoretically, first, complementing literature on online content consumption and engagement (Filippas & Horton, 2021), we are among one of the first to investigate users' content engagement across different newsfeed channels within the platform. Second, this study contributes to the literature on users' reactions to algorithmic recommendations (Holtz et al., 2020). Our findings indicate that users' social orientation and tenure on the platform affect their acceptance of algorithmic recommended content. Third, we extend social media research by focusing on a widely applied but less studied social network content composition, i.e., friends' liked content (Mattke et al., 2020). Practically, our findings offer strategic implications for social media platform operators on the newsfeed design.

Hypotheses Development

Selective Attention Theory

We rely on the selective attention theory and empirical findings about human-algorithm interactions to develop our hypotheses. The selective attention theory is a cognitive psychology theory regarding information processing (Treisman, 1969). It describes how people focus on particular signals in an information-heavy environment (Moore & Zirnsak, 2017). Upon the coming of the information, people allocate their attention based on information attributes, individual expertise, and goal-directedness. With years of development, the selective attention theory has been widely used in the consumption choice context. It also provides theoretical inspirations for various information system research in different contexts, for example, the design of personalization cues on websites, evaluations of user engagement status, and online market competition (Iyer & Katona, 2015).

Content Engagement Quantity – Entire Platform

The selective attention theory argues that individuals' total attention to certain information correlates with the information volume (Moore & Zirnsak, 2017). In our context, hiding friends' liked content will reduce the available information amount for users. Decreasing information availability reduces users' overall utility due to the increased searching cost for desirable content (Filippas & Horton, 2021; Xu et al., 2014). The loss of attention and utility discourage users' content engagement. Moreover, as a critical component of social network channels, friends' liked content has the prominent social endorsement and effects (Dewan et al., 2017; Tang et al., 2019). Thus, friends' likes serve as word of mouth and a quality signal of online content. Hiding friends' liked content will weaken these quality signals and then increases the cost of locating high-quality content, especially for users with less experience with the platform.

Additionally, socializing and information-seeking are two dominant driving forces for user online content engagement (Park et al., 2009). Goal-directedness is an important component of the selective attention theory; the inconsistency between information and goal will decrease people's attention allocation. For social-oriented users, engaging friends' liked content enables them to interact with other users on the platform, and it plays an important role in achieving their socializing goals. Therefore, hiding friends' liked content will reduce social-oriented users' content engagement volume on the platform. Summarizing the above discussions, we hypothesize that:

H1: Hiding friends' liked content from the newsfeed will decrease the quantity of users' content

Content Engagement Quantity – Across Channels

In addition to the overall quantity of content engagement, hiding friends' liked content from the newsfeed may influence users' content engagement across channels differently. In general, substitutional and complementary relationships may exist among newsfeed channels. On the one hand, all newsfeed channels compete for limited user attention (Iyer & Katona, 2015; Sismeiro & Mahmood, 2018). Users might switch their attention to other channels for desirable content, if the delivery of content in one channel gets restricted. On the other hand, newsfeed channels may complement each other due to the exposure effect (Sismeiro & Mahmood, 2018; Yang & Ghose, 2010). Specifically, when users are attracted and retained by friends' liked content, the inertia may spark users' interest in content from other channels (Aridor, 2022). The selective attention theory indicates that the potential substitution and complementary relationships between channels depend on channel characteristics, users' experience/expertise, and users' goals on the platform (Moore & Zirnsak, 2017). Next, we develop separate hypotheses about the impacts of hiding friends' liked content on user-content engagement in three discussed newsfeed channels: social networks, trending content, and algorithmic recommendations.

We consider the social network channel first, particularly friends' posted content. As discussed in the introduction of newsfeed channels, friends' posted and liked content are two components of the social network channel. These two types of content are both generated from users' self-formed interpersonal networks and share similar attributes; thus, they should have a high substitutional relationship (Aridor, 2022). First, friends' posted and liked content comes from users' immediate friends in the social network, reflecting friends' interests and activities. Engaging with such content is a critical means to interact with friends and satisfy users' socializing needs. Based on the selective attention theory, the attention freed by the absence of friends' liked content can be easily reallocated to content that achieves similar goals (Moore & Zirnsak, 2017). Second, the proximity of social networks suggests that content from user-formed networks is likely to align with their preference and interests. Social networks could play a filtering role in delivering content with desirable quality and content that suits users' preferences (Levy, 2021). When friends' liked content becomes less visible, users are likely to switch to the other social network channel (i.e., friends' posted content) to seek content that generally matches their interests. Notably, users with less experience with the platform tend to rely on the filtering role of social networks to locate high-quality content. Therefore, we hypothesize that:

H2a: Hiding friends' liked content from the newsfeed will increase the quantity of users' engagement with friends' posted content.

Interacting with trending content can also assist users in achieving their socializing goals. Peer/social influence is the common underlying force behind friends' liked content and trending content. Trending content exerts influence via the popularity effect and friends' liked content exerts influence via the proximity effect, these two channels both reflect human interactions (Dewan et al., 2017). Further, trending content can also serve as quality signals via the gatekeeping role (Yang & Peng, 2020). The popularity represents the crowd's interest and general evaluation on the content. Therefore, when social influence and quality signals are weakened due to the unavailability of friends' liked content, the users are likely to find trending content as a substitute. Formally, we hypothesize that:

H2b: Hiding friends' liked content from the newsfeed will increase the quantity of users' engagement with trending content.

The algorithmic recommendation channel has distinct attributes that differ from social networks and trending charts. While social networks and trending content are primarily driven by user-initiated activities and interactions, algorithmic recommendations are primarily driven by platform-controlled algorithms. Therefore, algorithmic recommendations mainly assist information-seeking but offer little in helping users achieve socializing goals. This pattern has been documented in the product recommendation context, where researchers find that algorithmic recommendations are more effective for utilitarian products that emphasize information dimensions and objective evaluations than hedonic products that emphasize human experience and interactions (Longoni & Cian, 2022). When the volume of friends' liked content is reduced on the newsfeed, social-oriented users will have less inertia to stay on the platform. This decreased inertia will make algorithmic recommendations receive less attention spillover from the social network channel (Aridor, 2022).

Additionally, as platform design and control recommendations, users might perceive them as manipulative and less trustworthy. Perceived manipulation can induce reactance and thus decrease users' attachment to the platform, especially for users with less experience and expertise with the platform (Zhang et al., 2022). In our studied context, when the platform limits users' access to friends' liked content and increases the presentation of recommendations on the newsfeed, users are likely to perceive this change as the platform's manipulative intent. They may think the platform poses restrictions on their autonomy in selecting desirable content. They, therefore, may develop stronger aversion and avoidance toward recommended content (Campbell, 1995; Dietvorst et al., 2015). Based on the above discussions, we hypothesize that:

H2c: Hiding friends' liked content from the newsfeed will decrease the quantity of users' engagement with algorithmic recommended content.

Content Engagement Diversity

When considering the influence of friends' liked content on consumption diversity, one of the direct consequences of hiding friends' liked content is the weakened social influence on the platform. Social influence is dominant in affecting user behavior in the online environment (Dewan et al., 2017). Users are more likely to perform herding activities to create a shared experience with online friends, feel included, and feel a sense of belonging in the community. After platforms disable friends' liked content from newsfeeds, it would be more challenging for the platform to persuade users to engage with more diverse content, especially content beyond users' interests or cross-cutting opinions.

Most importantly, the changes in user content engagement quantity in the previous section may further affect the engaged content diversity through the volume effect (Hosanagar et al., 2014; Lee & Hosanagar, 2019). Hosanagar et al. (2014) investigated user consumption diversity of digital music, and they found that increased consumption volume will significantly enhance users' exposure to diverse content and, ultimately, their consumption diversity. In our context, when users decrease their engagement volume on the platform, they also reduce their chance to expose to diverse content and therefore shrink their individual-level engagement diversity. Bear the above in mind, we hypothesize that:

H3: Hiding friends' liked content from newsfeed will decrease the diversity of users' content engagement

Research Context, Data, and Methods

Research Context: Zhihu

We test our research hypotheses in the context of Zhihu.com, the largest social Q&A platform and the equivalent of Quora in China. Zhihu has over 220 million registered users and 34 million daily active users. Users can follow each other to form their network on the platform. The majority of the content on Zhihu is organized in the question-and-answer format. By September 2020, Zhihu had accumulated more than 289.7 million answers[2]. The vast amount of content needs to be appropriately distributed to users. Illustrated in Figure 2, Zhihu simultaneously utilizes three representative channels for content distribution: *Follow* (user-formed social network), *Recommendation*, and *Trending* content. The *Follow* section delivers content posted and liked by friends from users' social networks. We refer to this channel as the social network channel. The *Recommendation* section delivers algorithm-generated personalized content to each user. The *Trending* section delivers real-time trending content to all users.

On December 17, 2020, Zhihu announced a policy change in their content presentation[3]. Friends' liked content was moved to a secondary tab and no longer displayed on the Follow newsfeed on the mobile application. Meanwhile, such change was not implemented on the Web application. This policy significantly reduced the visibility of friends' liked content for mobile app users. As a result, users need to make extra effort to track such content. In this study, we leverage this exogenous shock as a natural experiment to explore the influence of hiding friends' liked content on the quantity and diversity of users' content engagement across newsfeed channels.

Figure 2. A Snapshot of a Typical Zhihu User's Newsfeeds

[2] Source: https://sec.report/Document/0000950123-21-000169/ (last accessed: August 5, 2022)

[3] Source: https://www.zhihu.com/pin/1322963377392238592 (last accessed: August 5, 2022)

Data Collection and Variables

We construct a user-weekly level panel data of users' content engagement records. The observation window is from September 1 2020 to March 31 2021, i.e., three months before and after the policy change. In our observational period, we randomly sampled 34,246 users and recorded their voted content (a measurement of content engagement; more detail is discussed later in this section). We track the daily data and then aggregate the data to the user-weekly level. The panel data records 34,246 users' content engagement data in 30 weeks.

We determine the newsfeed channel of user-engaged content via the following steps. We first identify content delivered through social networks. To achieve this goal, we collect the followee list for each sampled user and identify 1.69 million users (friends) in our sampled users' social networks. Then, we collect all activity records of these 1.69 million users, including content directly posted by these users and content liked by these users. This leads to 11.5 million activity records of sampled users' social networks. If users voted a content that matches an activity record of their friends, we consider that used-engaged content was delivered through the social network channsel. This step identifies friends' posted and liked content. In the second step, we identify content that comes from the trending channel. We collect daily hot trend lists throughout the observation window. For the remaining content engagement records after the previous step, if the record belongs to that day's hot trend lists, we consider the content is delivered via the trending channel. Lastly, content from the recommendation channel is personalized for each user; therefore, we cannot directly collect them. However, as Zhihu mainly relies on the three discussed newsfeed channels to deliver content[4], once we identify content from social networks and trending lists, it is fair to assume that the rest of the content is distributed via algorithmic recommendations.

In this study, we measure the quantity of users' content engagement by the number of content users voted. The vote reflects a user's positive response toward a piece of content. It can be an appropriate proxy for users' active engagement with online content (Levy, 2021). Precisely, we construct a series of variables to measure the quantity of user-engaged content on the platform and each newsfeed channel. *Vote_All* is the number of content users voted on the entire platform. Note that the social network channel includes content posted and liked by online friends. We, therefore, differentiate these two types of content in our study. We use *Vote_SN_Liked* to indicate the number of voted content users' friends previously liked. This variable is expected to drop significantly after the policy change. We also use *Vote_SN_Posted* to measure the number of voted content users' friends posted. Additionally, we generate *Vote_Reco* to represent the number of voted content from algorithm recommendations. *Vote_Trend* is the number of voted content that comes from the trending lists.

To measure the diversity of user-engaged content, we first need to understand the content category on the studied platform. We employ the K-means clustering method to categorize user-engaged content and summarize the topic for each cluster. Specifically, we first follow a standard natural language processing procedure to clean all collected content, and then we use a Word2Vec model to represent each content with a 100-dimension vector. Next, we use K-means clustering to categorize content, and the elbow curve to indicate that three clusters are an ideal choice for content categorization for our study. We display the top ten keywords in each category in Table 1. We can see that Cluster 1 is mostly about science and IT knowledge. Cluster 2 mainly includes interpersonal communication and social topics. Cluster 3 is about liberal and art knowledge. Further, we label each user-voted content with its associated cluster and construct three variables (*Topic_Science*, *Topic_Social*, and *Topic_Liberal*) to measure the quantity of user-content engagement in each category in any given week. With these measures, we further calculate Blau's index (*Topic_Blau_Index*) to measure the diversity of user-engaged content. The computational formula of Blau's index is $1 - \sum p_k^2$, where p represents the proportion of the k^{th} cluster of content. A higher Blau's index represents higher diversity in users' content engagement. If a user did not consume any content on a given week, we set the value of *Topic_Blau_Index* to zero.

[4] Source: https://www.sec.gov/Archives/edgar/data/1835724/000119312521070815/d72883df1.htm (last accessed: August 5, 2022)

Content Category	**Topics in the Category**
Cluster 1 Science & IT Knowledge	Education, University, Academic, Math, the Internet, Smartphone, Coder, Graduate student, Technology, Physics
Cluster 2 Social Topics	Society, Daily life, Career life, Economics, Health, Relationship, Real experience, Emotion, Marriage, Interpersonal Communication
Cluster 3 Liberal & Arts Knowledge	History, Politics, Literature, Games, Films, Culture, Philosophy, Art, Countries, Religion

Table 1. Top Topics in Content Clusters

Last, to leverage the policy change, we identify a group of users (*Mobile_Group*) that mainly visit Zhihu through the mobile app and take these users as the treatment group. For each observation in the panel data, we use the *After_Policy* variable to represent whether an observation is after the policy implementation. The main independent variable, *Treat,* is the product of *Mobile_Group* and *After_Policy*. As we include user and week fixed effects in our analysis, the coefficients of *Mobile_Group* and *After_Policy* would be absorbed. Table 2 shows the definition and summary statistics of all variables in this study.

Variable	**Definition**	**Min**	**Max**	**Mean**	**St. Dev.**
$Mobile\_Group_i$	Dummy variable. 1 if user *i* is an intensive mobile user; 0, otherwise.	0	1	0.201	0.401
$After\_Policy_t$	Dummy variable. 1 if week *t* is after Zhihu's policy change; 0, otherwise.	0	1	0.500	0.500
$Treat_{it}$	Dummy variable. It is the product of Mobile_Group and After_Policy. 1, if a user *i* is influenced by the policy in week *t*; 0, otherwise.	0	1	0.100	0.301
$Vote\_All_{it}$	Count variable. It is the overall number of answers that user *i* voted in week *t*.	0	1,306	9.623	29.638
$Vote\_SN\_Liked_{it}$	Count variable. It is the number of answers from friends' likes that user *i* voted in week *t*.	0	660	2.547	10.160
$Vote\_SN\_Posted_{it}$	Count variable. It is the number of answers from friends' postings that user *i* voted in week *t*.	0	250	0.769	3.165
$Vote\_Trend_{it}$	Count variable. It is the number of answers from trending topics that user *i* voted in week *t*.	0	559	1.808	7.643
$Vote\_Reco_{it}$	Count variable. It is the number of answers from algorithmic recommendation that user *i* voted in week *t*.	0	1,051	4.499	15.942
$Topic\_Science_{it}$	Count variable. It is the number of science and IT knowledge-related answers that user *i* voted in week *t*.	0	314	1.558	5.440
$Topic\_Social_{it}$	Count variable. It is the number of social-related answers that user *i* voted in week *t*.	0	830	5.444	17.229

$Topic\_Liberal_{it}$	Count variable. It is the number of liberal and arts- related answers that user *i* voted in week *t*.	0	639	2.621	9.900
$Topic\_Blau\_Index_{it}$	Continuous variable. It is the Blau index of answers across topics that user *i* voted in week *t*.	0	1	0.193	0.247
$Following_i$	Count variable. It is the number of accounts that user *i* follows on Zhihu.	0	5824	399.7	776.914
$User\_Tenure_i$	Continuous variable. It is the number of years of user *i*'s experience with the platform.	0	9.756	3.680	2.237
Number of Observations: 1,027,380 (34,346 users * 30 weeks)					

Table 2. Variables and Summary Statistics

Empirical Model and Specification

As discussed earlier, the policy change only happens to the mobile app, and users did not expect or experience the policy before the announcement. This naturally-occurring exogenous variation allows us to identify the impacts of hiding friends' liked content on users' content engagement through a difference-in-difference (DiD) approach. We include individual user-level fixed effects in our models to control the existing time-invariant differences among users. Moreover, we include week-fixed effects in our models to eliminate the impacts of common temporal shocks. The two-way fixed effect models are specified as the following Equations (1) and (2):

$$DV_{it} = \alpha_i + \delta_t + \beta_1 Treat_{it} + \varepsilon_{it} \tag{1}$$

$$DV_{it} = \alpha_i + \delta_t + \beta_1 Treat_{it} + \beta_2 Treat_{it} * Moderator_i + \varepsilon_{it} \tag{2}$$

In these Equations, DV_{it} indicates the quantity and diversity of user-engaged content. α_i and δ_t are user and week fixed effects, respectively. Moreover, we include a series of moderators in Equation (2) to explore underlying mechanisms and heterogeneity effects.

Empirical Results

Content Engagement Quantity

In this subsection, we present the effects of hiding friends' liked content on the quantity of users' content engagement. Table 3 summarizes the estimation results of the DiD analysis specified by Equation (1) with log-transformed engagement quantity as dependent variables. Column (1) in Table 3 reports the result when the dependent variable is *$Vote\_All_{it}$*. The negative and significant coefficient (-0.034; $p < 0.01$) indicates that users engaged 3.34% (e^-0.034 - 1) less content on the platform when friends' liked content is unavailable on the newsfeed. This result supports our hypothesis H1.

Column (2) in Table 3 reports the result with *$Vote\_SN\_Liked_{it}$* as the dependent variable. The policy change directly influences the visibility of friends' liked content. The negative and significant coefficient (-0.057; $p < 0.01$) confirms the effectiveness of the studied policy change. Moving friends' liked content to a second-order tab indeed increases the access cost and reduces users' engagement with such content.

Next, we place emphasis on the influence of the implemented newsfeed policy on users' content engagement in other channels. The estimated coefficient in Column (3) is positive but insignificant (0.002, p=0.13), suggesting that users' engagement with friends' created content did not change significantly after hiding friends' liked content. We only find weak evidence for our H2a. One possible reason for the weak marginal increase is the relatively small volume of friends' posted content compared to content from other channels. The limited variation space makes it difficult to observe significant changes in users' engagement with friends' posted content.

DV	Vote_All	Vote_SN_Liked	Vote_SN_Posted	Vote_Reco	Vote_Trend
	(1)	(2)	(3)	(4)	(5)
Treat	-0.034***	-0.057***	0.002	-0.021***	0.007***
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
Week FE	Y	Y	Y	Y	Y
User FE	Y	Y	Y	Y	Y
No. Observations	1,027,380	1,027,380	1,027,380	1,027,380	1,027,380
R^2	0.733	0.738	0.614	0.672	0.649

Table 3. Quantity of User-Content Engagement

Notes: 1. Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01

2. All dependent variables are log-transformed.

Regarding the influence of the policy change on user-content engagement in algorithmic recommendation and trending channels, Table 3 Column (4) indicates that when people get less content from their social network (friends' liked content), they reduce their engagement with algorithm-recommended content (-0.021, p<0.01). In contrast, the estimated coefficient in Column (5) is positive and significant (0.007, p<0.01). Users engaged more with trending content after the policy change. Thus, we find evidence that supports our H2b and H2c.

DV	Vote_SN_Liked_Frac	Vote_SN_Posted_Frac	Vote_Reco_Frac	Vote_Trend_Frac
	(1)	(2)	(3)	(4)
Treat	-0.021***	0.003***	0.004***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
I (Vote_All > 0)	0.168***	0.086***	0.593***	0.153***
	(0.001)	(0.0004)	(0.001)	(0.001)
Week FE	Y	Y	Y	Y
User FE	Y	Y	Y	Y
No. Observations	1,027,380	1,027,380	1,027,380	1,027,380
R^2	0.467	0.229	0.641	0.332

Table 4. Content Consumption Proportion across Channels

Notes: Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01

The opposite direction of the policy's effects on the algorithmic recommendation and trending channels is interesting. One potential reason for the opposing changes is that trending and social network channels are driven by user activities and imply user interests. In contrast, algorithmic recommendations reflect the platform control and intended guidance. Thus, the trending channel can better satisfy users' socializing needs on platforms compared to the algorithmic recommendation channel. When friends' liked content becomes unavailable on the newsfeed, users tend to seek content from other similar user-driven sources, thus, leading to increased content consumption in trending content. These results further reveal that recommendation and social network channels are not necessarily competing for users' limited attention but complementary to each other. The social network and trending content channels can partially substitute each other.

To investigate how users relatively shift their attention across channels, we also look at the fraction changes in users' engagement in each channel. Taking the engagement fraction as dependent variables, we again estimate Equation (1) for this analysis. Meanwhile, to account for the case where the fraction is unable to calculate due to zero engagement in a week, we include a dummy variable (i.e., $I\ (Vote\_All > 0)$) in Equation (1) to indicate whether a user engaged with any content in a week. The results are reported in Table 4. From this table, we can see that after hiding friends' liked content on the newsfeed, as expected, users significantly decreased their consumption proportion of friends' liked content. Meanwhile, users shift more attention to other channels. Notably, the trending channel sees the highest attention increase after the policy change. Together with the results in Table 3, we find that users tend to substitute social network channel with trending channel that also offers user-driven content. The fraction results provide additional evidence to support H2a, H2b, and H2c.

Content Engagement Diversity

In this subsection, we estimate the impact of friends' liked content on the diversity of user-engaged content. We again estimate Equation (1) with the constructed measure *Topic_Blau_Index* as the dependent variable. Like previous proportion analysis, we also included the non-empty consumption dummy. The estimated coefficient in Column (1), Table5, is negative and significant (-0.005, p<0.01). It indicates that users' content engagement becomes less diverse when they expose less to friends' liked content.

DV	**Topic_Blau_Index**	
	(1)	(2)
Treat	-0.005***	-0.004***
	(0.001)	(0.001)
I (Vote_All > 0)	0.183***	0.174***
	(0.0004)	(0.0004)
Vote_All		0.001***
		(0.00001)
Week FE	Y	Y
User FE	Y	Y
No. Observations	1,027,380	1,027,380
R^2	0.599	0.608

Table 5. Content Consumption Diversity

Notes: Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01

Moreover, as the engagement diversity is correlated with quantity (Lee & Hosanagar, 2019), we control the overall engagement quantity, *Vote_All*, in the analysis and report results in Column (2), Table 5. Note that the estimation coefficient of *Vote_All* is positive and significant. This result is consistent with Lee and Hosanagar (2019), revealing that higher consumption quantity leads to increased consumption diversity. Together with the results in Section 4.1, the decreased consumption diversity can be partially attributed to the reduced consumption volume. Moreover, the estimation of the key independent variable, *Treat*, remains negative and statistically significant (-0.004, p <0.01) with decreased magnitude (from -0.005 to -0.004). This result implies that the social network might be a more effective channel for engaging users with diverse content.

Mechanism Exploration

This subsection explores the mechanisms proposed in the hypotheses development section. The selective attention theory argues that goal-directedness and individual expertise are important factors in attention allocation. We operationalize these two factors in our context and conduct moderating analyses.

User Goal-directness

Users' goals (e.g., socializing or information-seeking) may drive the results of changes in content engagement across different channels (Park et al., 2009). Users with a stronger socializing orientation on the platform are more likely to disengage from the platform when the platform reduces the visibility of social network-driven content. And social-oriented users are likely to perceive algorithmic recommendations as manipulative and show a stronger aversion toward them. We, therefore, conduct a heterogeneity analysis on users' socializing orientation to test this mechanism.

We measure a user's socializing orientation by the number of accounts a user follows. This measurement is commonly used to operationalize people's social intentions. We include the variable, $Following_i$, in Equation (2) as the moderator and conduct the analyses. Results are reported in Table 6. The marginal effects of *Treat* conditional on the log-transformed following count, *Log_Following*, are illustrated in Figure 3.

DV	Vote_All	Vote_SN_Liked	Vote_SN_Posted	Vote_Reco	Vote_Trend	Topic_Blau_index
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.008	0.091***	-0.007	-0.008	-0.123***	0.006**
	(0.013)	(0.009)	(0.007)	(0.011)	(0.009)	(0.003)
Treat*Following	-0.005**	-0.028***	0.002*	-0.002	0.025***	-0.002***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Week FE	Y	Y	Y	Y	Y	Y
User FE	Y	Y	Y	Y	Y	Y
No. Observations	1,027,380	1,027,380	1,027,380	1,027,380	1,027,380	1,027,380
R^2	0.733	0.739	0.614	0.672	0.649	0.599

Table 6. Moderating Effects (Following Count)

Notes: 1. Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01

2. Dependent variables in columns (1) to (5) and Following are log-transformed.

We notice several findings. First, the significant and negative estimations of the interaction term in Column (1) and Figure 3(a) show that in the post-treatment period, users' overall content engagement drops more as their following count increases. As expected, Column (2) shows that users who follow more accounts on the platform experience larger decrease in their engagement with friends' liked content after the policy change. Figure 3 (b) indicates that the effect of implemented policy becomes negative and significant when a user follows more than 20 users (e^3). More than 95% of all users fall into this group. What's more, Columns (3), (5) and Figures 3(c) and 3(e) display that users who follow more accounts are more likely to increase their engagement with friends' posted content and trending content. Further, users' social orientation negatively moderates the results about user engagement with algorithmic recommendations. The interaction term in Column (4) is negative but insignificant. However, from Figure 3(d), we can still observe a trend that users with more friends on the platform engage less with algorithm recommendations after implementing the new newsfeed policy.

Furthermore, we examine the moderating effect of user social-orientation on the diversity of user-engaged content. The estimated result in Table 6, Column (6), indicates that the diversity of user-engaged content decreased significantly (-0.002, p<0.01) as users followed more accounts. The marginal effect graph, Figure 3(f), also shows that when a user followed more than around 90 (e^4.5) accounts, the diversity of user-engaged content significantly decreased after hiding friends' liked content. Together with the results on engagement quantity, we can see that users' goals play a critical role in their response to the newsfeed change. The continual content engagement of social-oriented users strongly relies on social network-driven content. And this content dependency is difficult to be substituted with algorithmic recommendations.

User Expertise

Further, we examine how users' expertise with the platform moderates the influences of friends' liked content on user-content engagement. Users' expertise with the platform can be operationalized as user tenure (Liu et al., 2020). Compared to new users, experienced users master better skills in navigating the content on the platform. They generally have more exposure to platform recommendations and higher algorithmic literacy. Therefore, experienced users should be less affected by the newsfeed changes on social media platforms.

DV	Vote_All	Vote_SN_Liked	Vote_SN_Posted	Vote_Reco	Vote_Trend	Topic_Blau_index
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.071***	-0.048***	-0.013***	-0.064***	-0.011**	-0.006***
	(0.006)	(0.004)	(0.003)	(0.006)	(0.005)	(0.001)
Treat*UserTenure	0.009***	-0.002**	0.004***	0.011***	0.005***	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)
Week FE	Y	Y	Y	Y	Y	Y
User FE	Y	Y	Y	Y	Y	Y
No. Observations	1,027,380	1,027,380	1,027,380	1,027,380	1,027,380	1,027,380
R^2	0.733	0.738	0.614	0.672	0.649	0.599

Table 7. Moderating Effects (User Tenure)

Notes: 1. Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01

2. Dependent variables in columns (1) to (5) are log-transformed.

We include the variable *Tenure* in Equation (2) as the moderator. Table 7 displays the estimation results, and Figure 4 illustrates the marginal effects conditional on user tenure. These results show that user tenure can effectively mitigate the negative influences of hiding friends' liked content on user content engagement. Specifically, the overall engagement quantity will increase by 0.9% as user tenure increases by one year. Moreover, we observe that users with longer tenure are more likely to seek more content from other channels to substitute for the reduction of social network-driven content. Remarkably, users' engagement with the algorithm-recommended content increases by 1.1% as users' tenure increases by one year. Figure 4(d) illustrates that users with more than five years of experience (around 30% of all users) increase their engagements with algorithmic recommended content and show less aversion to the algorithmic channel after the policy change.

Regarding the engagement diversity, the estimation of the interaction term in Table 7 Column (6) is positive but insignificant (0.0004, p=0.206). However, from Figure 3(f), we can still observe that hiding friends' liked content will not significantly influence the diversity of content engagement for users with more than 7.5 years of experience on the platform.

Overall, our results support our theoretical arguments that users with more platform expertise possess better skills in navigating content through different newsfeed channels. Moreover, regarding the quantity and diversity of subsequent content engagement, these users show higher tolerance to newsfeed curation change. Compared to new users to the platform, experienced users are more receptive to platform-recommended content, which suggests the mitigating effect of algorithm literacy in algorithm aversion (Burton et al., 2020).

Robustness Check

Relative Time Model

To validate our findings, we conduct a series of robustness checks. Since we apply the DiD approach in this research and the effective DiD design requires the treatment and control groups to have similar trends before the exogenous shock. Violating the parallel trend assumption would result in invalid estimations. We follow the common practice and undertake the relative time model to check the parallel trend assumption (Angrist & Pischke, 2008). We include a series of time dummies to indicate the relative week distance between an observation and the policy implementation week. Equation (3) displays the model specification for relative time analysis.

$$\mathrm{DV}_{it} = \alpha_i + \delta_t + \sum_{j=-5}^{j=10} \beta_j T_j + \varepsilon_{it} \# (3)$$

In Equation (3), T_j denotes the relative week dummies. α_i and δ_t capture the user and week fixed effects, respectively. We set one week before (j = -1) the policy implementation as the baseline period. Under the parallel trend assumption, the estimated coefficient for the time dummies before the policy change should be insignificant. Our results (available upon request due to page limitation) indicate that most of the estimations of T_j before the relative week 0 are insignificant in all the models. Thus, our DiD analyses satisfy the parallel trend assumption.

Propensity Score Matching

To alleviate the concern that the results are driven by inherent differences between web and mobile app-intensive users, we conducted the propensity score matching (PSM) to construct a balanced and comparable sample. We include a series of user characteristics and activity records before the newsfeed policy implementation to conduct the PSM, including user tenure, created-content quantity, consumption quantity, follower count, and followee count. We perform all analyses on the matched sample again and report the results in Table 8. Overall, most results remain qualitatively consistent with our main analyses.

DV	**Vote_All**	**Vote_SN_ Liked**	**Vote_SN_ Posted**	**Vote_Reco**	**Vote_Trend**	**Topic_ Blau_index**
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.027***	-0.047***	0.005**	-0.014***	0.002	-0.005***
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)
Week FE	Y	Y	Y	Y	Y	Y
User FE	Y	Y	Y	Y	Y	Y
No. Observations	407,940	407,940	407,940	407,940	407,940	407,940
R^2	0.726	0.737	0.608	0.659	0.643	0.504

Table 8. Matched Sample Results

Notes: 1. Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01

2. Dependent variables in columns (1) to (5) are log-transformed.

Discussions and Conclusions

This research investigates the impacts of hiding friends' liked content on users' content engagement across newsfeed channels. We take advantage of an exogenous platform change (i.e., hiding friends' liked content from the newsfeed) on a social media platform and conduct a series of empirical analyses. Our results indicate that users engage with less content on the entire platform after the policy change. Regarding the relative attention spent, users shift more attention to algorithmic recommended and trending content. The magnitude of attention shift toward the trending channel is larger than the change in the algorithmic recommendation channel. Due to the significantly decreased engagement volume on the platform, the quantity of users' engagement with algorithmic recommended content was reduced. Furthermore, user-engaged content becomes less diverse when friends' liked content is unavailable in the newsfeed.

Theoretical Implications

First, this study enriches the research stream of the attention economy in the context of social media (Aridor, 2022; Filippas & Horton, 2021). We take a novel perspective by exploring users' attention allocation across different newsfeed channels within the platform. Previous research mainly investigates users' content engagement on the entire platform or in a specific channel (Levy, 2021). We extend this research stream by showing that newsfeed channels are interrelated. Our results suggest that social networks and algorithmic recommendations complement each other. The trending channel can partially substitute the social network channel. Moreover, previous theoretical research primarily focuses on content quality, creator characteristics, and audience allocation (Bhargava, 2022; Filippas & Horton, 2021) when modeling users' engagement decisions. Our findings contribute to that past research by highlighting the importance of newsfeed channels in this process.

Second, our work contributes to the broad human-algorithm interaction literature. Numerous researchers have studied the role of algorithmic recommendations in product and media consumption (Bakshy et al., 2015; Holtz et al., 2020; Lee & Hosanagar, 2019). We extend this stream of work by looking at the interplay between human-driven channels (social networks and trending) and the algorithmic recommendation channel. We empirically show that users tend to transfer their attention between human-driven channels rather than from human-driven to algorithmic recommendation channels. Notably, human-driven and algorithmic recommendation channels are not necessarily competing against each other for user attention. Users' engagements with algorithmic recommendations can partially come from users' attention spillover from the social network channel. Additionally, our findings complement research on algorithm aversion. It is easier for users' attention to transfer across human-driven channels (social networks and trending) than from human-driven channels to algorithmic recommendations.

Third, this study also enriches the theoretical understanding of the role of social networks in the diversity of users' content engagement. We extend past research by focusing on a widely applied but less studied social network-driven content and newsfeed channel, i.e., friends' likesd content (Mattke et al., 2020). Some research concerns that friends' liked content might lead to polarized content engagement and low engagement diversity due to homophily and herding effects (Bail et al., 2018; Levy, 2021). Our work shows the critical role of friends' liked content in boosting the quantity and diversity of user-engaged content. Our findings indicate that reduced access to social network-generated content will narrow users' attention to limited topics and result in less diverse online content consumption.

Practical Implications

Our results generate several aspects of managerial implications for platform practitioners. First, our research empirically examines that friends' liked content is very effective for social media in engaging users. Displaying friends' liked content on newsfeeds can motivate users to consume more social media content. Additionally, it stimulates users to engage with more platform-recommended content. Although platforms can guide more user attention to their recommended content by limiting users' access to their social network-generated content, this strategy will backfire as users' overall engagement level drops.

Moreover, our results also generate societal implications for platform managers and policymakers. Although there has been a heated discussion on the potential threat from social networks, our results suggest that exposing content shared through social networks does not necessarily constrain users' content choice to limited topics. In contrast, restricting access to social network-driven such as friends' liked content will lead users to engage with less diverse content. This consequence is alarming to platform managers and policymakers if they aim to enhance users' exposure to diverse content and opinions. To reach this goal, platform managers should boost user engagement by enabling access to social network-generated content.

Last but not least, our results further reveal that social-oriented users are more vulnerable to the changes in social network-driven content, as indicated by their greater reduction in quantity and diversity of content engagement. Platforms should focus on curating and promoting social network-based content to retain such users. Moreover, longer-tenured users present a receptive attitude toward algorithmic recommendations. Platforms should invest effort in growing and maintaining tenured users, especially for platforms if their revenue model relies on users' responses to recommended content.

Limitations and Future Directions

Our research is not without limitations. One of the weaknesses is that the total amount of content exposed to a user is not available. We, therefore, proxy user content engagement by only the content that the user voted. This measure is ideal for capturing users' actively and heavily consumed content, but it may not fully represent all the content they have received. Therefore, answering questions such as changes in content conversion rates across newsfeed channels would be challenging.

Second, our current research only studies the quantifiable changes in users' content engagement. However, more nuances at the content level are worthy of further exploration. For example, in the product consumption scenario, prior literature has documented user perception of the algorithmic recommendation and its effectiveness in promoting different products (Longoni and Cian 2022). In the context of online content, future researchers can apply natural language processing techniques to understand the fit between content types and newsfeed channels.

Third, our results indicate that reducing social network-driven content would decrease diversity in user-engaged content. The characteristics of users' social networks might moderate this result. Specifically, the reduced content diversity might be more pronounced for users whose friends have diverse interests. Future researchers can consider advancing this work by investigating the moderating effect of users' social network characteristics.

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