Exploring the Effects of Event-induced Sudden Influx of Newcomers to Online Pop Music Fandom Communities: Content, Interaction, and Engagement

QINGYU GUO, The Hong Kong University of Science and Technology, China
CHUHAN SHI, The Hong Kong University of Science and Technology, China
ZHUOHAO YIN, The Hong Kong University of Science and Technology, China
CHENGZHONG LIU, The Hong Kong University of Science and Technology, China
XIAOJUAN MA*, The Hong Kong University of Science and Technology, China

Online fandom communities (OFCs) provide a convenient space for fans to create, collect, and discuss the content of their mutual interest (e.g., music artists). Real-world events could frequently attract outsiders to join OFCs, providing both the opportunity to expand the fan base and challenges to manage the community. However, it is unclear that how influxes of newcomers would influence the development of OFCs and what user behaviors may be correlated with their future engagement. To fill this gap, we took the music OFCs as the focus, and quantitatively analyzed user behaviors and their correlations with users' future engagement in the community. Results suggested that 1) event-induced newcomers expressed more hate speech and negative sentiment, praised less celebrity-related content (e.g., song, album), and interacted with narrower cohorts than existing members; 2) Although existing members tended to receive more upvotes during the events than before and after the events, newcomers showed an opposite trend; 3) keeping users' activeness, expressing positive sentiments, and having diverse interactions during periods of influx were helpful when maintaining members' future levels of engagement. This work deepened the understanding of fan behaviors in the dynamic period, and we discussed how our insights could benefit OFCs.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**.

Additional Key Words and Phrases: Online fandom community, interaction behaviors, content analysis, user engagement

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*Corresponding author

Authors' addresses: Qingyu Guo, qguoag@connect.ust.hk, The Hong Kong University of Science and Technology, Hong Kong, China; Chuhan Shi, cshiag@connect.ust.hk, The Hong Kong University of Science and Technology, Hong Kong, China; Zhuohao Yin, zyinad@connect.ust.hk, The Hong Kong University of Science and Technology, Hong Kong, China; Chengzhong Liu, chengzhong.liu@connect.ust.hk, The Hong Kong University of Science and Technology, Hong Kong, China; Xiaojuan Ma, mxj@cse.ust.hk, The Hong Kong University of Science and Technology, Hong Kong, China.

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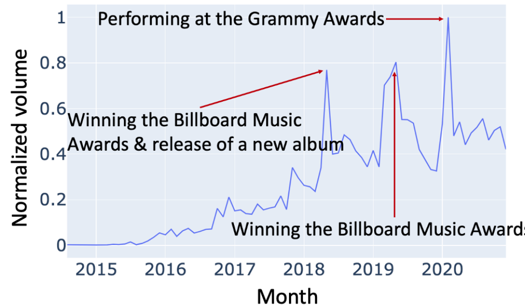


Fig. 1. Monthly active newcomer volume from the founding of each Reddit community, to the end of 2020. The data were derived from the PushShift API. In the figure, the "normalized volume" (range: 0 – 1) stands for the daily newcomer number divided by the maximum number of daily newcomers in the plotted period.

1 INTRODUCTION

Online fandom communities (OFCs) provide convenient virtual networking spaces for fans with a common interest in someone or something [89]. An OFC is usually built around some aspect of popular culture such as idols [42, 68], brands [9], and sports teams [89]. Empowered by the rapid development of social media in recent years, certain news concerning an event in a subculture may reach a broader audience beyond its original fan base, sparking people to join the associated fandom community serendipitously to share information and express emotion [39]. In such a case, the OFC can suddenly attract attention and participation from the public, which may lead to an event-triggered surge of new members. Such events can frequently arise in OFCs in the entertainment industry [72], in the sense that intervals between events can be as short as a few weeks. Taking the Reddit OFC associated with the Bangtan Boys [71], one of the most popular K-pop bands, as an example. Events such as the band receiving an award or releasing a new album often draw in a large number of new members over a short period (Figure 1).

The influx of newcomers triggered by events offers the opportunity to expand the fan base, which is valuable for OFCs [42, 68]. However, previous works suggested that masses of new members may also create a nuisance and consequently hinder the success of general online communities [33]. While Ringland et al. [72] identified that events could attract outsider's attention to OFCs, we know relatively little about to what extent the influx of newcomers may affect OFCs, and the relationship, if any, between member behaviors and their future engagement. Such knowledge is important as it could deepen the understanding of fan behaviors in a dynamic period. The resulting insights are also helpful for community moderators to regulate OFCs, expand the fan base, and strengthen community resiliency against the potential negative impacts of surges of newcomers [43, 59].

While existing literature studied the impact of massive community newcomers caused by (involuntary) platform updates or promotions [33, 43, 59], our target phenomenon (i.e., influx of newcomers in OFCs triggered by real-world events) differs in: 1) a higher frequency of newcomer influxes [72] (as illustrated in Figure 1), 2) more complex composition (e.g., fans and anti-fans [32]) and dynamics (e.g., toxic behaviors like bullying [68]), and 3) a stronger tendency of shifting discussions from casual communication to an event-related topic [47, 59].

This paper aims to characterize the behavior of newcomers and existing members in OFCs during the event-induced influx periods and explore factors that may impact their future engagement through quantitative analysis. To this end, we used music OFCs as a case for their representativeness in fan studies [73]. In particular, we chose OFCs on Reddit because these communities are managed and driven by fans (e.g., posts, comments, and received upvotes), providing the opportunity to explore the intrinsic behaviors of fans and the resilience of OFCs under events [89]. In contrast, OFCs on other platforms (such as Weibo and Twitter) are heavily influenced by agency-guided accounts in terms of steering member interactions and regulating content (e.g., comment filtering and ranking) [63, 81].

In this work, we first extracted data from 23 music fandom communities before 2021, and then identified 51 events that induced influxes of newcomers in these communities; these formed the MusicEvent Dataset. Through this dataset, we sought answers to the following research questions: **RQ1)** What are the differences in engagement, discussion topics, and interaction patterns between newly attracted members and existing members in these fandom communities during the events? **RQ2)** How might the engagement behavior, discussion topics, and interaction patterns of different user cohorts change within and outside of the event periods? **RQ3)** How might event-induced influxes affect users' future engagement in fandom communities?

Our results showed that newcomers drawn in by events were more likely to express hate speech and negative sentiment, praised less celebrity-related content (e.g., album, song), and interacted with narrower cohorts than existing members during the events. The interaction between users appeared to be more diverse and evenly distributed with surges of newcomers in OFCs compared with that during the ordinary period. Existing members tended to receive more upvotes during the events than before and after the events; however, an opposite relation existed for newcomers. Also, we observed that users' activeness, expressed sentiment and the interaction diversity during the influx period were positively correlated with their future engagement. This work added to the empirical understanding of fan behaviors and future engagement in the dynamic periods. Our findings have implications for OFCs to seize the chance to grow their fan base while managing potential negative impacts in the face of an event-triggered influx of newcomers.

2 RELATED WORK

2.1 Online Fandom Community

The term "fandom" refers to a group of media fans who have a common interest in a particular topic, such as music, movies, celebrities, sports teams, and public figures [16]. Online fandom communities (OFCs) provide convenient virtual spaces for fans of mutual interest to gather together, sharing a culture of content transformation, content curation, and socialization [24, 72]. The content transformation stands for OFC members' act of generating and sharing creative fanworks, such as writing fiction inspired by books or films (e.g., Harry Potter) [21, 22] and remixing of music and videos [72]. It is a kind of informal learning based on collective interests and inspirations [10, 25]. In this process, fans may find mentors through online interactions, build connections with each other, and develop their social identity within the community [10, 23]. As content transformation may require certain creation skills, it is more common for OFC members to engage in jointly curating the content of their shared interests, such as gathering news, managing wikis [64], and maintaining playlists of music artists [72]. Collection and exchange of high-quality content in OFCs enable existing fandom members to consolidate trust within the community and strengthen their sense of attachment [48]. Such collective knowledge construction also helps newcomers of an OFC to quickly become familiar and closely resonate with the fan topics of interest [72]. Moreover, fans socialize in OFCs to establish affinities and affections [54, 72], which generally results in strong cohesion [42]. For example, OFCs are known to be a supportive space for marginalized people [19, 20] and aid members in overcoming frustrating moments [72].

Despite the unity within fan communities, there might also exist conflicts. Fans from different OFCs might have opposite stands, resulting in toxic content and conflicts in OFCs [68, 90]. Meanwhile, various parties (such as fans and anti-fans) exist in a fandom community, and anti-fans may radically cyberbully other members in OFCs or even the community-associated celebrity [34].

Moderating such abusive actions has been a haunting concern for the moderators in popular social media platforms [13]. For OFCs, regulating the community content is especially important; otherwise, massive negative (and even toxic) content may threaten the trustful and supportive relationship among community members and hurt the image of the common interest (e.g., the celebrity), consequently impairing members' engagement in OFCs [24, 72]. Therefore, we conducted a set of quantitative analyses to deepen the empirical understanding of the impact of the event-triggered influx of newcomers on the discussed content, interaction, and engagement in OFCs.

2.2 Music Fan Behavior

Music has been playing a critical role in human culture development for a long time [67]. Celebrities in the music industry can attract fans from all over the world [68]. Similar to other fandoms, content transformation (such as creating memes and music mashups) and curation (e.g., collecting images related to celebrities with certain themes) are popular activities in music OFCs [72, 73]. Meanwhile, music fans are often more passionate than members of other types of fandoms, sharing a culture of supporting their beloved artists [49]. For example, music fans could contribute to the success of artists in a variety of ways, such as voting for their favorite artists for an award and promoting them among the general public [42]. Music fans also show strong mutual support in the community. In particular, Lee et al. [54] showed that the fandom of BTS gives people a sense of being understood and comforted, thus helping them maintain positive mental states. Ringland et al. [72] also suggested that OFC members establish a strong bonding with each other, which is positively correlated with their mental wellness. By supporting each other, members find the OFCs to be a place of love and belonging [73]. Due to their massive size and strong community cohesion, music fans are capable of making broad and profound impacts in the real world [55, 68]. For instance, ARMY (fans of BTS) hosted a crowdfunding campaign to support the Black Lives Matter movement, and they ended up donating more than one million US dollars [68].

In this work, we chose the music fandom community as a case to explore the effect of events on OFCs for several reasons. First, while both pop culture (e.g., music) and sports fandoms are representative fandom genres, the fan base of the former is broad and diverse (e.g., compared with male-dominated sports fans) [77], which provides a lens to investigate how diverse members interact during the events. Second, compared with other pop culture fandoms, music OFCs are representative in sharing a mixed culture of content transformation, content curation, and socialization. By contrast, content in other pop culture OFCs might be less varied; for instance, content transformation dominates the activities in the fanfiction community [23]. Third, celebrities in the music industry tend to engage in frequent, somewhat irregular real-world events, such as releasing songs and albums, holding concerts, and receiving awards, which periodically attract public attention. Therefore, an event-triggered influx of newcomers is a common and representative phenomenon in music OFCs.

2.3 Newcomers and Online Community Evolution

An influx of newcomers is one of the keys to online community evolution [17]. Compared with the existing members, newcomers may have different behavior patterns [59], for example, they may have higher expectations for the support from the community [66]. Although newcomers bring new perspectives to communities [37], they may also produce a negative impact. For example, in September 1993, the accessibility of the first Internet community, Usenet, was given to all people instead of just university students due to a system flaw. As a result, an unprecedented quantity of new users flooded into Usenet, which broke the community norms and caused immense disorder, a phenomenon also known as the "Eternal September" [33]. Prior studies on similar cases suggest that a huge influx of newcomers may cause information overload [41], which might lead to lower-quality content [31]. A recent incident of an "Eternal September" happened in 2013 when several communities on the Reddit platform were changed to a default mode so that new visitors would automatically subscribe to these communities. As a result, large influxes of new members appeared shortly after the setting was changed [43]. Lin et al. [59] quantitatively compared the content and interaction patterns before and after the system change in these Reddit communities and concluded that a sudden increase in newcomers tended to make members cluster around a small portion of content while the community linguistic identities remained similar to before. Kiene et al. [43] suggested that the well-coordinated moderation and technology to mitigate norm violations may help overcome the negative effects caused by the sudden influx of newcomers. However, compared with the newcomer influxes caused by changes in platform settings, newcomers triggered by breaking events appeared more frequently in online communities [88]. Since community members are more likely to discuss around a central topic when facing breaking news [5], more conflict may emerge. Therefore, understanding the impact of massive event-induced newcomers on online communities and proposing response mechanisms would benefit community management. Furthermore, the existing works only considered general online communities. It is still unclear whether the mass of newcomers would influence OFCs and whether the influences may be different from those on other communities due to the special characteristics of fandom communities.

3 DATASET

Our dataset was derived from music OFCs on Reddit. We firstly selected 23 music OFCs on Reddit. Then we crawled comments and replies related to these communities before 2021 via the PushShift API [4], gathering raw data of the MusicFandom Dataset. Based on this dataset, we identified 51 unique events that induced influxes of newcomers in these communities between 2018 and 2020, which formed our MusicEvent dataset.

3.1 Select Music OFCs on Reddit

At first, a list of the well-known pop music artists was generated from three of the most popular music awards, namely the Grammy Awards, Billboard Music Awards, and the American Music Awards in the year 2018 – 2020. The winners and nominees for the aforementioned formed a candidate list and we kept only those whose associated OFCs still had regular interactions among fans during the crawled period on Reddit. Moreover, we filtered out communities that were founded after 2017 to ensure there were enough existing members to compare with the newcomers. Based on our observation, communities with less than 10k subscribers rarely had discussion threads of the associated celebrities. Therefore, we further excluded these communities for fair analysis. Finally, we selected 23 active online communities corresponding to popular pop music artists, and collected data of each community from the founding of the community to the end of 2020. In total, there are 6,451,523 comments, 842,171 submissions, and 519,728 unique users in the collected dataset.

3.2 Identify Events that Induce Influxes of Newcomers

We further identified dynamic periods triggered by the events that induced influxes of newcomers in the OFCs. We firstly applied the peak detection algorithm to this data following existing work [14, 62]. The algorithm calculated the moving average and variance within a sliding window across the time series, and detected periods with fluctuation of daily newcomer numbers larger than a threshold in each community. We leveraged the algorithm to reduce the search range of periods of interest, which were the time intervals of event-induced influxes of newcomers.

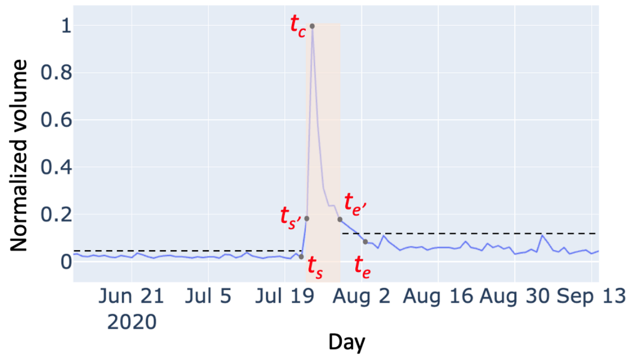


Fig. 2. An example of event duration adjustment. In the figure, the "normalized volume" (range: 0 − 1) stands for the daily newcomer number divided by the maximum number of daily newcomers in the plotted period. The blue line tracks the newcomer number each day within the selected time window. The dotted line on the left signals the maximum daily newcomer number in the week before the event period, while the one on the right signals that in the week after the event period. t_c denotes the day when the daily newcomer number reaches the climax. t_s and t_s' represent the last day before the event period and the first day of the event period, respectively. t_e and t_e' denote the first day after the event period and the last day of the event period, respectively.

Then we further verified whether the sudden influx of newcomers during these periods was indeed triggered by real-world events. We recruited three volunteers who were familiar with pop music (2 males, 1 female). They firstly discussed and selected popular platforms that contain news of pop music celebrities, including Wikipedia [84], Pitchfork [70], Billboard [6], and MusicBrainz [65]. Wikipedia is an influential source of information about various topics (e.g., music, sports, etc.) [26]. Pitchfork and Billboard are premier music websites, which publish extensive music reviews, news and gossip [57]. MusicBrainz is one of the largest public databases of music metadata [79].

These websites served as external knowledge bases to facilitate the identification of event-induced influxes of newcomers. Next, two of the volunteers divided the candidate periods proposed by the peak detection algorithm equally. For each candidate period, they independently queried about the aforementioned resources to check whether there were reports of events related to the corresponding pop music artist that happened in that time window. If no real-life event could be matched to the given period, the data was discarded from further analysis. If multiple events took place in that period, they selected the one closest to the climax of daily newcomer number in the specified time span. Finally, the third volunteer examined all periods identified by the two volunteers in the previous step to guarantee the existence of the events during those periods. Among all of the algorithm-proposed periods, 51 of them could be mapped to at least one event.

Next, we adjusted the start and end time of each period to a fine-grained level according to the exact date of the event and the changes in daily newcomer number. Specifically, we determined the start time by traversing back from the climax of each period according to the daily newcomer number, until we found day t_s when the number is less than at least one day in its previous one week. Then, day t_s' following day t_s is set as the start time. We adopted similar criteria to find the end day. We traversed from the climax day of each period to the future time, until we found day t_e when the newcomer number is less than at least one day in its following week. Then, day t_e' before day t_e is denoted as the end time. As shown in Figure 2, t_s and t_e are the closest points to climax day while satisfying the criteria of the number of daily newcomers being less than at least one day a week away from climax, which implies that t_s' and t_e' are not such points. From this observation, it can be further concluded that daily newcomer number before the climax day is greater than any day in one week before the start time, and the number of daily attracted newcomers after the climax day is greater than any day in one week after the end time.

To comprehensively understand the effects of surges of newcomers on the user behavior in the community, we further extracted the data two weeks prior to each event, and one week following the event. To study behavior discrepancies between user cohorts (see next subsection) during the event, we defined phase C as the event period. To analyze the topic in RQ2, we introduced two more phases: phase B and D respectively refer to 1 week before the event and 1 week after the event. For analysis in RQ3, we further defined phase A to be the second week before the event. Refer to Figure 3 for an overall illustration.

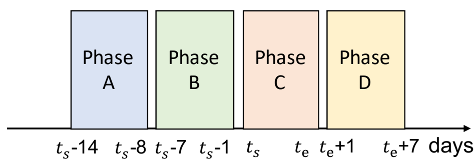


Fig. 3. Event phases definition.

3.3 User Cohort

Table 1. Statistics for the collected Reddit data and identified events.

Data description	Total (mean/std)	Phase A (mean/std)	Phase B (mean/std)	Phase C (mean/std)	Phase D (mean/std)
#users	27,132/22,718	810.5/823.7	892.2/1051.2	2,316.5/2,835.1	1,213/1,265.8
#posts	36,616/37,797	310.1/334	388.7/678.7	1,110.3/2,077	498/591.4
#comments	280,501/347,917	2,531.9/3,853.7	3,063.9/5,519.3	12,276/24,698	3,799.6/5,052.2

Detailed data statistics regarding different phases can be found in Table 1. To ensure the data quality, we only considered members who had at least one contribution in the OFCs between 2018 and 2020. The statistical results for lifetime distribution showed that around 70% of members made less than 5 activities then left the community, and less than 60% of members stayed in the community for over 3 months. Moreover, for existing members who had interactions in the community before the event period (phase C), less than 65% of them made 5 contributions. Therefore, we categorized the community members into three user cohorts: **Newcomer**: A user that joins the community for the first time during the selected period. A user is considered to join the community when he or she submits the first post or leaves the first comment. **Returnee**: A user that is neither a newcomer nor a core fan in the community. Specifically, a user that has joined this community before the selected period and made less than 5 contributions within 3 months before the selected period. **Core Fan**: A user that has made at least 5 contributions within 3 months before the selected period, where "contributions" refers to posts or comments.

To clarify, user cohorts can be viewed as identities of users, which may switch across phases. For instance, a newcomer in phase C who made adequate contributions can transform to a core fan in phase D because implicitly, in phase D, this user no longer joined the community for the first time. Such switches of user cohort introduce the transition graph in Figure 4, which depicts the transitions of users among different cohorts over the phases. According to the transition graph, the cohort of newcomers inflated during phase C and deflated during phase D, with 11.3% of newcomers switching to other cohorts in phase D; while in phase A and phase B, more than 15% of newcomers switched to other cohorts in the following phases.

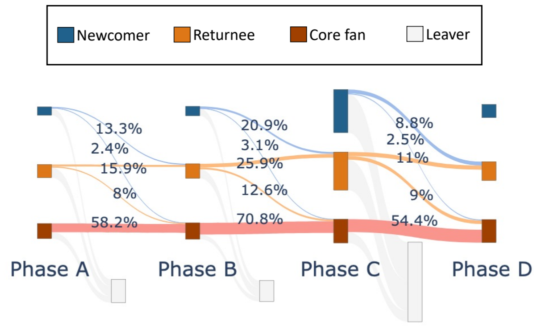


Fig. 4. User transitions over the phases. In this figure, the blue, orange and red blocks indicate different user cohorts, and the gray blocks are "Leaver" groups indicating users that were inactive in the next phase. Links between blocks signal transfers of user cohorts, and the percentages on them indicate the proportion of users in a certain cohort, who transferred to another cohort (can keep the same) in the next stage. For example, 13.3% and 2.4% of the newcomers in phase A become returnees and core fans in phase B, respectively.

4 METHOD

To answer the three RQs, we developed a series of features to represent community members' behavior. We also adopted several analytical techniques, such as the Latent Dirichlet Allocation (LDA) modeling for content analysis, statistical tests, and regression analysis.

4.1 Feature Extraction

In a Reddit community, users can initiate posts or leave comments under others' posts. We quantified member behaviors from three aspects, namely engagement features, sentiment features, and interaction features. For the engagement features, we calculated relevant features including the total number of comments and posts, as well as average upvote scores. As essential attributes of OFCs, such features are also adopted by Zhang et al. [90] as approaches to investigating user engagement patterns in NBA forums. For the sentiment features, we adopted the VADER [35], which is commonly used for sentiment analysis on social media. As for the interaction features, we adopted the method proposed by Yang et al. [86] to obtain the social network based on the users' posting and commenting behaviors. We summarized all the features in Table 2.

4.2 Analytic Techniques

To analyze the discussed topic in RQ1 & RQ2, we first trained a model for topic modeling by using Latent Dirichlet Allocation (LDA) [8]. LDA is an unsupervised model commonly used to discover the hidden topic in the corpus [38]. The basic assumption of the LDA model is that each document – the user comment in our case – is generated from a topic distribution, and that words which appear in the document follow the word probability in each topic. To train the LDA model, a parameter k is predefined, which stands for the number of topics in the entire corpus (i.e., all user comments in our case). During the training process, the LDA model learns the probability of words associated with each topic (topic-word distribution) and the probability of a topic in each document (document-topic distribution). The output of the LDA model is k groups of words (each represents a topic) and the topic distribution in each comment, which requires researchers to further identify the topic theme(s). Following the procedures in [11, 80, 87], we performed topic modeling on all comments in the MusicEvent dataset, and varied the number of topics k of the LDA model from 2 to 20. The final topic number was selected as five based on the coherence

Table 2. Features extracted for OFC analysis. In the table, "Avg." stands for "Average".

Category	Features	Description	Reference
Engagement	# comments	total number of comments a member makes in each phase of each event	Zhang et al. [90]
	# posts	total number of posts a member makes in each phase of each event	
	Avg. upvote score	average upvote score over a member's comments in each phase of each event	
Sentiment	Avg. expressed sentiment	average VADER compound score of comments and posts of a member	VADER [35]
	Avg. received sentiment	average VADER compound score of responses sent to a member	
Interaction	In degree	number of replies from other community member	Yang et al. [86]
	Out degree	number of replies sent to other community member	
	% in degree from each cohort	percentage of comments received from a user cohort	
	% out degree to each cohort	percentage of the comments sent to a user cohort	
	In degree entropy	level of user-user interaction distribution regarding receiving messages	
	Out degree entropy	level of user-user interaction distribution regarding sending messages	

score [74]. Two researchers, who are music fans of western pop singers, derived the topic via an inductive approach. They first independently assigned labels to each of the five topics according to the associated words and the original comments with high probability in them. Then they compared and consolidated the topic themes as listed in the "LDA topic" column in Table 3. Note that the LDA model learns the probability (range: 0-1) of words in each topic, rather than assigning each word to only one topic. Therefore, a word may appear in multiple topics [11] as the same word could have different meanings given the context. We refer to the original context to deal with the word sense disambiguation of duplicated keywords.

Table 3. Topics and associated words in the MusicEvent dataset.

LDA topic	Associated words
1- Praise for song or album	*song, like, album, love, listen, really, well, feel, sound, best*
2- Community construction	*post, please, yes, comment, thank, message, subreddit, question*
3- Informal conversation	*fuck, shit, lmao, bro, yeah, oh, man, good, lol*
4- Hate speech	*nigger, hate, anyone, guys, work, country*
5- Album release	*get, album, time, drop, day, come, release, music, year*

In RQ1, we aimed to find dimensions of the topic that show great differences between newcomers and existing members. To do that, we firstly used the Mann-Whitney U test [61] to find dimensions of the topic that show significant differences between cohorts, then quantified the differences in each dimension via Cohen's d, an implementation of calculating effect sizes [15]. In RQ2, we adopted a similar strategy for interpreting to what extent events would impact the discussed topic in each cohort. We compared each dimension of the topic vector in each user cohort between phase B and C, as well as phase C and D, and further calculated Cohen's d on dimensions that show significant differences. For other metrics, we conducted a series of Mann-Whitney U test to investigate the differences across user cohorts during the events in RQ1, and the differences between within and outside the event periods of each user cohort in RQ2. To better interpret the results, we further reported the effect size Cohen's d.

In RQ3, we included representative features in RQ1 and RQ2. We adopted regression analysis to analyze the correlation between future engagement and 1) joining periods 2) user cohorts.

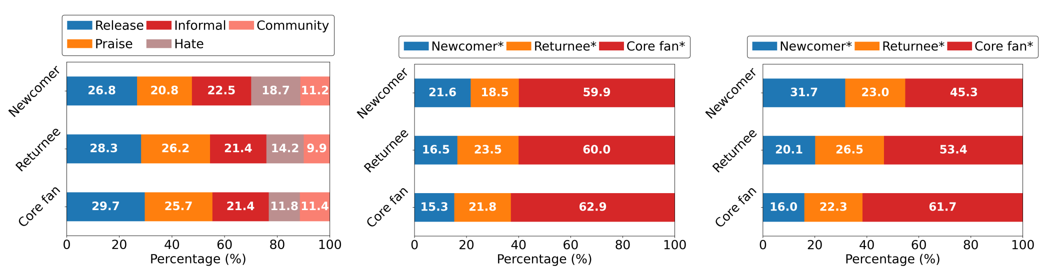
We selected several features that show significant differences in RQ1 and RQ2. The independent variables in our regression models were the same, including: 1) Engagement Features: daily activity, mean upvote score; 2) Sentiment Features: average received sentiment, average expressed sentiment; 3) Interaction Features: in degree entropy, out degree entropy. Daily activity features were calculated by dividing the activity number (sum of comments and posts) over the duration of phases, in order to mitigate the impact that the durations are distinct in different events. The dependent variable in all regression models was the next week engagement, quantified by the activity number in the following week of each member. All features were continuous variables and were standardized by mean centering and dividing by two standard deviations following the recommended practice [28]. We further calculated each feature's variance inflation factor (VIF) to check their multicollinearity. All VIFs were smaller than three, suggesting that there was no multicollinearity issue in our regression analysis.

5 ANALYSIS AND RESULT

In this section, we unfold the RQs and conduct an in-depth analysis of the RQs we have proposed.

5.1 RQ1. Engagement of Various User Cohorts during Influx Period

In this section, we analyze and compare the community engagement of the three user cohorts during the newcomer influx periods, particularly in terms of topic distribution, posting/commenting behavior, and intra-community interaction.



(a) Discussion Topic distribution. (b) User out degree distribution. (c) User in degree distribution.

Fig. 5. Figure 5a shows the average value of topic distribution in the comment of each user cohort during the events. A larger value represents more comments related to the target category. "Release " stands for the topic of "album release", "Praise" stands for "praise for song or album", "Informal" stands for "informal conversation", "Hate" stands for "hate speech", and "Community" stands for "community construction". For example, 26.8%, 20.8%, 22.5%, 18.7%, and 11.2% of the content made by newcomers were in the topic of "album release", "praise for song or music", "informal conversation", "hate speech", and "community construction", respectively. Figure 5b and 5c demonstrates the average value of out and in degree distribution for each user cohort during the event. We used the "*" to distinguish the central node and other nodes. For instance, in Figure 5b, 21.6%, 18.5%, and 59.9% of newcomers' replies were sent to (other) newcomers, returnees, and core fans, respectively; similarly, in Figure 5c, 31.7%, 23.0%, and 45.2% of newcomers' replies were received from (other) newcomers, returnees, and core fans, respectively.

5.1.1 Topic Distribution. Figure 5a demonstrated the topic distribution for each user cohort during the event period (phase C). It can be observed that "album release" was the most frequently discussed topic for all user cohorts. The significant test and effect size showed that newcomers had the greatest significant differences from existing members on the topic of "hate speech" (core fan: $U = 18{,}401{,}336{,}109$, $p < 0.001$, $d = 0.36$; returnee: $U = 10{,}688{,}428{,}313$, $p < 0.001$, $d = 0.22$) and "praise for song or album" (core fan: $U = 22{,}573{,}108{,}473$, $p < 0.001$, $d = 0.18$; returnee: $U = 11{,}201{,}014{,}347$,

Table 4. Mean and standard deviation of the engagement of newcomers, returnees and core fans in our selected OFCs during phase C. All significant tests are compared with newcomers. ***:$p < 0.001$; **:$p < 0.01$; *:$p < 0.05$. In the table, "Avg." stands for "Average".

		Newcomer (mean/std)	Returnee (mean/std)	Core fan (mean/std)
Engagement	# comments	3.87/17.59	3.53/11.30 ***	10.73/37.68 ***
	# posts	0.30/0.75	0.33/0.85	1.06/3.42 ***
	Avg. upvote score	3.84/22.92	4.94/29.90 ***	5.15/25.02 ***
Sentiment	Avg. expressed sentiment	0.087/0.27	0.105/0.26 ***	0.116/0.22 ***
	Avg. received sentiment	0.057/0.18	0.071/0.20 ***	0.102/0.19 ***
Interaction	In degree	2.17/13.39	2.58/26.49 ***	12.99/278.26 ***
	Out degree	3.84/17.54	3.5/11.25 ***	10.63/37.39 ***
	In degree entropy	0.21/0.44	0.25/0.48 ***	0.5/0.58 ***
	Out degree entropy	0.23/0.45	0.31/0.50 ***	0.62/0.57 ***

$p < 0.001$, $d = 0.21$). This indicated that newcomers attracted by events were less likely to praise the celebrity-related content (e.g., song, album) and were more likely to deliver hate speech in comparison to the existing members.

5.1.2 Intra- and Inter-Cohort Interaction. According to the values of in degree and out degree in Table 4, although newcomers replied significantly more to others' posts than returnees (U = 943,190,512, $p < 0.001$, $d = 0.02$), the amount of replies newcomers received was significantly fewer than that of returnees (U = 982,449,216, $p < 0.001$, $d = 0.02$). We further examined the degree entropy of user nodes in each cohort. A larger degree entropy of a node indicated that the corresponding user interacted with more diverse user groups. Results showed that both the in degree entropy (core fan: U = 472,183,751, $p < 0.001$, $d = 0.59$; returnee: U = 1,001,853,563, $p < 0.001$, $d = 0.09$) and out degree entropy (core fan: U = 413,105,598, $p < 0.001$, $d = 0.78$; returnee: U = 964,313,320, $p < 0.001$, $d = 0.17$) of newcomers were significantly less than those of existing members, suggesting that newcomers seemed to have fewer inter-cohort interactions than existing members in the event periods. For a deeper look into which type of users the comment were directed to or received from, depicted in Figure 5b and Figure 5c, core fans dominated most of the incoming and outgoing edges (> 45%) of each user cohort in sending or receiving messages, which is in accordance with the finding of Lin et al. [58]. For each cohort, the level of intra-cohort interaction was greater than any cross-cohort interaction for both in degree or out degree. For instance, Figure 5b shows that during the event, newcomers' out degree proportion to other newcomers was significantly higher than both returnees (U = 787,235,726, $p < 0.001$, $d = 0.15$) and core fans (U = 514,286,837, $p < 0.001$, $d = 0.19$). This result may be explained by the "echo chamber" effect [36], which means that even during a highly dynamic period, members were still inclined to discuss with those of similar status in the community.

5.1.3 Activity Behavior. As illustrated in Table 4, the newcomers in the examined OFCs initiated significantly fewer posts than core fans (U = 529,091,646, $p < 0.001$, $d = 0.36$) during influx periods, but such difference was insignificant compared with returnees (U = 1,036,827,498, $p = 0.16$, $d = 0.04$). Though newcomers left significantly fewer comments compared with core fans (U = 362,201,864, $p < 0.001$, $d = 0.26$), they were significantly more active than returnees (U = 944,434,917, $p < 0.001$, $d = 0.02$). On the one hand, this result echoed our definition of "core fans" as they indeed made the most contributions to their communities. On the other hand, it also suggested that newcomers were not the least active type of users in an OFC according to these two metrics.

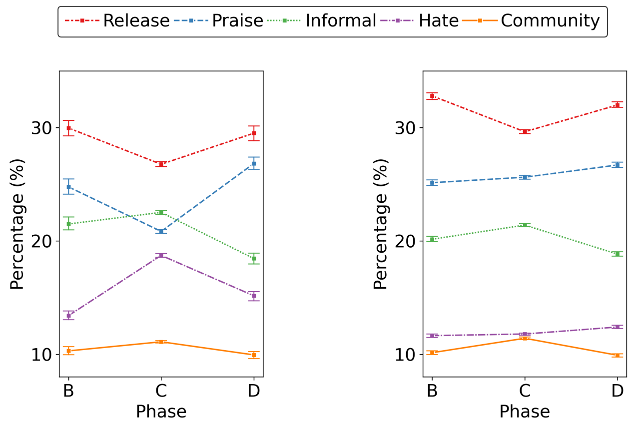
Previous work suggested that sudden influxes of newcomers may bring low-quality content into the community [31, 59]. To assess the quality of content in the scenarios that we investigate, we applied the same quantitative measurement, average score, adopted in [59]. As the average score was the mean of the received upvote scores of all comments and posts from a given user cohort, a large average score may indicate the content was well received by the community. Overall, the average score of newcomers who joined during the events was significantly lower than existing members in phase C (core fan: U = 489,833,898, p < 0.001, d = 0.06; returnee: U = 933,084,049, p < 0.001, d = 0.04), and the content of core fans were the most well-received. We further examined the sentiment expressed and received by members, the key factor in building a healthy and "playful" social environment in OFCs [72]. We found that during the influx period, newcomers were more likely to express negative sentiment than core fans (U = 569,623,969, p < 0.001, d = 0.12) and returnees (U = 987,636,541, p < 0.001, d = 0.07), and were less likely to receive positive sentiment than them (core fan: U = 523,203,687, p < 0.001, d = 0.24; returnee: U = 995,812,371, p < 0.001, d = 0.07). These results again showed that core fans remained the key contributors to OFCs during such dynamic periods.

5.1.4 Summary. Overall, during the event-induced influx periods, newly joined members were involved in different discussion topics and demonstrated different interaction patterns from existing fans in the communities. Newcomers were more likely to use hate speech and express negative sentiment, praised less about the song or album, and communicated with narrower cohorts than existing members. Moreover, newcomers received fewer upvote scores than existing members. As for user activity, though newcomers were more active in replying to others compared with returnees, they initiated fewer posts than the core fans. Although there were influxes of newcomers during the events, core fans still dominated the communication according to activity quantity, content quality, and interaction analysis.

5.2 RQ2. Event-Induced Effect on User Engagement

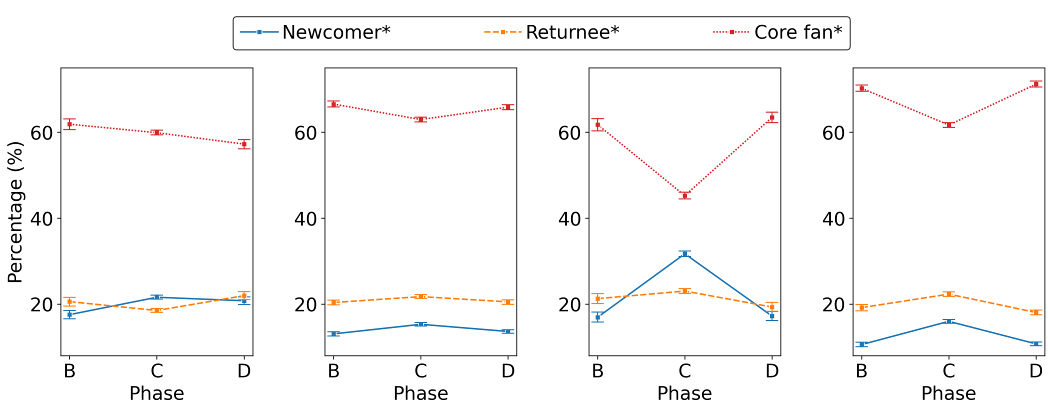
We seek to understand whether the event-induced influx of newcomers would change the initial engagement status of an OFC, and whether such changes, if any, would sustain after the influx. To answer the former question, we extracted the same set of engagement features as in RQ1 from a one-week time window right before the event periods (phase B) and compared them to those extracted during the event periods (phase C). To address the latter question, we compared engagement features in phase C with those derived from a one-week time window immediately after the event period (phase D). We present our findings as follows.

5.2.1 Topic Distribution. Figure 6a and Figure 6b presented the topic distribution of newcomers and core fans in phase B (before the event), C (the event period), and D (after the event). We found that compared with newcomers who joined OFCs in phase B, newcomers in phase C discussed significantly less content in the topic of "praise for song or album" (U = 1,414,814,919, p < 0.001, d = 0.16), but significantly more content in the topic of "hate speech" (U = 1,294,682,534, p < 0.001, d = 0.24). The result indicated that unlike newcomers who joined the OFCs in the ordinary period, newcomers attracted by the events were more likely to circulate content that may be more toxic and were less likely to praise the celebrity-related content. We also observed that the impact of event on newcomers' negative content may not last long. For instance, newcomers who joined OFCs in phase D expressed significantly more (U = 1,743,651,336, p < 0.001, d = 0.24) content in the topic of "praise for song or album", but significantly less (U = 1,651,919,753, p < 0.001, d = 0.16) content in the topic of "hate speech" than newcomers joined in phase C. Meanwhile, except for the topic of "community construction", the Cohen's d on the expressed topics for existing members were generally smaller than that of newcomers when comparing the topic distribution between phase B and C, as well as phase C and D, indicating that existing member generally maintained the topic identity.



(a) Topic distribution change for newcomers. (b) Topic distribution change for core fans.

Fig. 6. The change of discussion topic for newcomers and core fans. The error bar stands for 99.9% CI. In Figure 6a and Figure 6b, "Release " stands for the topic of "album release", "Praise" stands for "praise for song or album", "Informal" stands for "informal conversation", "Hate" stands for "hate speech", and "Community" stands for "community construction". In each phase, the sum of percentage of the topics is 1. For instance, Figure 6a shows that in phase B, on average, 30.0%, 24.8%, 21.5%, 13.4%, and 10.3% of the content made by newcomers were in the topic of "album release", "praise for song or music", "informal conversation", "hate speech", and "community construction", respectively. Returnees shared similar trends with core fans as of the change of topic distribution.



(a) Out degree distribution change for newcomers.

(b) Out degree distribution change for core fans.

(c) In degree distribution change for newcomers.

(d) In degree distribution change for core fans.

Fig. 7. The change of in and out degree distribution for newcomers and core fans. The error bar stands for 99.9% CI. In Figure 7a and 7b, each line stands for the percentage of replies sent to each user cohort (i.e., newcomers ("Newcomer*" in the legend), returnees ("Returnee*" in the legend), and core fans ("Core fan*" in the legend)). We use the "*" to distinguish the central node and other nodes. For instance, Figure 7a demonstrates that on average, newcomers in phase B left 17.6%, 20.6%, and 61.8% of their replies to other newcomers, returnees, and core fans, respectively. In Figure 7c and 7d, each line stands for the ratio of replies received from each user cohort. For example, Figure 7c illustrates for newcomers in phase B, on average, 16.9%, 21.3%, and 61.8% of the received replies came from other newcomers, returnees, and core fans, respectively. Returnees shared similar trends with core fans as of the change of in and out degree distribution.

Table 5. Mean and standard deviation of the engagement of newcomers, returnees and core fans during phase B, C and D in our selected OFCs. All significant tests are compared with the previous phase. ***:$p < 0.001$; **:$p < 0.01$; *:$p < 0.05$. "Avg." stands for "Average".

User Cohort	Features		Phase B (mean/std)	Phase C (mean/std)	Phase D (mean/std)
Newcomer	Engagement	# comments	1.70/3.87	3.87/17.59 ***	1.51/3.12 ***
		# posts	0.38/0.86	0.30/0.75 ***	0.39/0.71 ***
		Avg. upvote score	4.49/29.54	3.84/22.92 ***	4.36/32.10 **
	Sentiment	Avg. expressed sentiment	0.105/0.28	0.087/0.27 ***	0.126/0.28 ***
		Avg. received sentiment	0.065/0.19	0.057/0.18	0.071/0.20 ***
	Interaction	In degree	1.73/4.92	2.17/13.39 ***	1.61/4.82 ***
		Out degree	1.66/3.86	3.84/17.54 ***	1.48/3.07 ***
		In degree entropy	0.16/0.39	0.21/0.44 ***	0.15/0.38 ***
		Out degree entropy	0.14/0.37	0.23/0.45 ***	0.14/0.36 ***
Returnee	Engagement	# comments	1.85/3.17	3.53/11.30 ***	1.74/2.79 ***
		# posts	0.29/0.76	0.33/0.85 ***	0.29/0.65
		Avg. upvote score	4.69/26.84	4.94/29.90 ***	4.54/24.86 ***
	Sentiment	Avg. expressed sentiment	0.118/0.29	0.105/0.26 ***	0.132/0.29 ***
		Avg. received sentiment	0.068/0.20	0.071/0.20 ***	0.073/0.21 **
	Interaction	In degree	1.76/5.02	2.58/26.49 ***	1.73/5.54 ***
		Out degree	1.82/3.16	3.50/11.25 ***	1.72/2.75 ***
		In degree entropy	0.16/0.38	0.25/0.48 ***	0.16/0.38 ***
		Out degree entropy	0.18/0.40	0.31/0.50 ***	0.19/0.40 ***
Core fan	Engagement	# comments	5.84/14.45	10.73/37.68 ***	5.19/11.50 ***
		# posts	0.60/1.89	1.06/3.42 ***	0.52/1.42 ***
		Avg. upvote score	4.95/21.85	5.15/25.02 ***	5.08/24.61 ***
	Sentiment	Avg. expressed sentiment	0.124/0.25	0.116/0.22	0.133/0.25 ***
		Avg. received sentiment	0.096/0.21	0.102/0.19 ***	0.100/0.21 ***
	Interaction	In degree	9.22/400.54	12.99/278.26 ***	4.59/12.74 ***
		Out degree	5.76/14.26	10.63/37.39 ***	5.11/11.18 ***
		In degree entropy	0.30/0.47	0.50/0.58 ***	0.29/0.47 ***
		Out degree entropy	0.44/0.53	0.62/0.57 ***	0.44/0.54 ***

5.2.2 Interaction Pattern. We found that both the out degree entropy (newcomer: U = 234,761,805, $p < 0.001$, $d = 0.20$; returnee: U = 308,469,827, $p < 0.001$, $d = 0.28$; core fan: U = 204,323,104, $p < 0.001$, $d = 0.32$) and in degree entropy (newcomer: U = 246,476,085, $p < 0.001$, $d = 0.11$; returnee: U = 324,669,927, $p < 0.001$, $d = 0.20$; core fan: U = 201,753,143, $p < 0.001$, $d = 0.37$) of all user cohorts increased significantly from phase B to phase C (as listed in Table 5). These suggested that surges of newcomers may stimulate communication between different types of users, and the interaction became more evenly distributed during the events than in the ordinary period.

We further investigated how the tendency of interaction cohorts was affected in the influx period. Figure 7a showed the out degree distribution of newcomers in phase B, C, and D. Newcomers in phase C had significantly higher (U = 165,638,708, $p < 0.001$, $d = 0.11$) out degree proportion to other newcomers compared with newcomers who joined OFCs in phase B. Existing members also shared a similar trend. For instance, as shown in Figure 7b, from phase B to phase C, there was a significant increase (U = 197,034,977, $p < 0.001$, $d = 0.09$) in core fans' out degree proportion to newcomers. Similar trends on the variation of in degree distribution can be found in Figure 7c and 7d. There was a significant increase in the proportion of received reply from (other) newcomers for both newcomers (U = 45,663,973, $p < 0.001$, $d = 0.39$) and core fans (U = 97,666,707, $p < 0.001$, d =

0.22) when moving from the ordinary phase B to the influx phase C. These results showed that all user cohorts were more likely to interact with newcomers in the influx period than in the ordinary period. Similar to the previous results, such change in the diversity of interacted cohorts and in and out degree distribution generally disappeared as the event periods reached an end.

5.2.3 Activity Behavior. We list the mean and standard deviation of the selected variables of each user cohort in the three periods (i.e., before (B), during (C), and after (D) event) in Table 5. Although the average upvote score of returnees (U = 333,748,817, p < 0.001, d = 0.01) and core fans (U = 230,983,269, p < 0.001, d = 0.01) increased significantly from phase B to phase C, that of newcomers actually dropped significantly (U = 249,560,783, p < 0.001, d = 0.03). This result suggested that the content produced by newcomers tended to be less received by community members in the influx period than before. The average score of the newcomer cohort climbed back in phase D, while the average score of existing members received declined, indicating a temporal change in the received upvote score. Moreover, we found that messages sent by newcomers (U = 248,290,902, p < 0.001, d = 0.07) and returnees (U = 345,829,634, p < 0.001, d = 0.05) bore significantly more negative sentiment during the influx periods (phase C) than one week before (phase B), while such a difference was insignificant for core fans (U = 245,146,742, p = 0.17, d = 0.03). In other words, during the dynamic period, only the core fans seemed to maintain a rather consistent sentiment in their messages. Similar to the topic distribution and user interaction, the influence on the expressed sentiment would not last for a long period. When moving from phase C to phase D, the expressed sentiment increased significantly after the influx periods ended (newcomer: U = 332,611,094, p < 0.001, d = 0.14; returnee: U = 428,739,428, p < 0.001, d = 0.10; core fan: U = 333,987,513, p < 0.001, d = 0.07).

5.2.4 Summary. Newcomers attracted by events presented a different topic distribution from newcomers who joined in the ordinary periods, and the former received fewer upvote scores than the latter. Meanwhile, existing members seemed to receive more upvote scores during the event than in the ordinary period. Moreover, the change of in and out degree entropy across phases suggested that the community interaction was more diverse and evenly distributed during the influx period than in the ordinary period. In addition, the expressed sentiment varied in different periods and across user cohorts. Together with the findings presented in the previous section, these results showed that influxes of newcomers triggered by events could result in short-term changes in user engagement, and such influences often would not last after the events.

5.3 RQ3. Prediction of Next-Week Engagement in the Ordinary Period and after the Influx Period

To address RQ3, we proposed a series of regression models, Model 1 - Model 6, to predict users' next-week engagement during an ordinary period (i.e., phase A predicting phase B) as well as right after an influx period (i.e., phase C predicting phase D). Model 1, 3, 5 stand for the regression models in the ordinary period, while model 2, 4, 6 represent the regression models after the influx period.

5.3.1 Engagement. As shown in Table 6, user's daily activity was positively correlated with next-week engagement in all models. This suggested that users who were more active in the current phase, regardless of the cohort or whether the influx period, were more likely to participate in community discussion in the next week. In contrast, the coefficients on average upvote score showed no significance to next-week engagement in all models, indicating that the perceived content quality may not be the critical factor to keep members staying in the selected OFCs.

5.3.2 Sentiment. Model 1 and Model 2 suggested that during the influx period, newcomers who expressed more positive sentiment and received more positive sentiment were positively correlated

Table 6. Regression coefficients of RQ3 models for predicting whether event-induced influxes would affect users' next-week engagement in fandom communities. ***:$p < 0.001$; **:$p < 0.01$; *:$p < 0.05$. "Avg." stands for "Average". "A. I." represents the regression models for predicting future engagement after the influx period.

User cohort	Newcomers		Returnee		Core fans	
	Model 1 (Ordinary)	Model 2 (A. I.)	Mode 3 (Ordinary)	Model 4 (A. I.)	Model 5 (Ordinary)	Model 6 (A. I.)
Daily Activity	0.5060 ***	0.0257 ***	0.3930 ***	0.1896 ***	2.7965 ***	2.1020 ***
Avg. Upvote Score	0.0047	-0.0033	0.0033	-0.0028	0.0049	0.0284
Avg. Received Sentiment	-0.0173	0.0085 **	-0.0001	0.0064	-0.0790 **	0.0506 ***
Avg. Expressed Sentiment	-0.0038	0.0068 *	-0.0186 **	0.0080 *	-0.0916 ***	0.0475 **
In Degree Entropy	-0.0134	0.0478 ***	-0.0494 ***	0.0334 ***	-0.1239 ***	0.0134
Out Degree Entropy	-0.0023	0.0715 ***	-0.0192 *	0.0564 ***	-0.0422	0.1833 ***
Intercept	0.0923 ***	0.0401 ***	0.0847 ***	0.0604 ***	0.6847 ***	0.5166 ***
R^2	0.225	0.029	0.163	0.069	0.367	0.445

to higher engagement in the next week. By comparing the coefficients of expressed sentiment for returnees in Model 3 and Model 4, as well as for core fans in Model 5 and Model 6, the expressed sentiment showed the opposite effects on existing members' future engagement. These results indicated that sentiment should be carefully considered in the music OFCs, especially during the influx period. Although negative sentiment does not significantly hinder engagement for all cohorts, it would impede future engagement for active members during the influx period.

5.3.3 Interaction. Model 2, 4, 6 demonstrated that the out degree entropy was positively correlated with higher engagement after the influx period for all user cohorts with significance. The result indicated that having diverse interactions across cohorts is beneficial for communities to keep members in the OFC during the influx period.

5.3.4 Summary. Our regression models showed that, daily activity was a robust indicator for predicting next-week engagement for all cohorts, regardless of the influx period. During the influx period, receiving positive sentiment, expressing positive sentiment, and having diverse interactions might be the stimulus for keeping future engagement levels for all user cohorts.

6 DISCUSSION

In this work, we explored the effects of the influx of newcomers triggered by events on OFC dynamics through the lens of music OFCs on the Reddit platform. Through quantitative analysis, we extended the empirical understanding of fan behaviors and future engagement in the dynamic period. We summarize the main findings and situate our results with prior works.

First, we found that surges of newcomers driven by events are likely to bring negative content to OFCs. Specifically, newcomers attracted by events were more likely to express hate speech and negative sentiment, and were less likely to praise celebrities-related content (e.g., album, song) than existing members during the events. These results are in line with prior works [33, 50] that newcomers may break community norms and hinder community development. However, such findings are inconsistent with the case where community content quality remains similar after surges of newcomers joining Reddit communities due to a change in the platform setting [59]. This may be due to complex relations existing in OFCs (e.g., fans and anti-fans [32, 90]), and surges of newcomers may exacerbate the conflict [51]. Another possible reason is that the communities promoted by platforms often have strong regulations to mitigate conflicts [43], indicating OFCs may strengthen regulations to help mitigate the negative effects of the influx of newcomers.

Second, we learned that the interactions between users were seemingly more diverse and evenly distributed with surges of newcomers in OFCs compared with that during the ordinary period. This finding is inconsistent with a prior study, which suggested that the community members were more inclined to exchange information and opinions with credible members during political events than in normal periods [58]. Although users often cared about information sources (e.g., credibility) in online discussions during events [60], the evenly distributed interaction in OFCs may suggest that members were curious about exchanging information and enjoyed building relationships with users in different cohorts in OFCs [72]. We also noticed that newcomers interacted with narrower user cohorts than existing members during the events. This was in line with a finding about online software collaboration platforms where newcomers often felt it was more difficult to build connections with core members [78].

Third, while prior work also found that there could have been a sudden drop in the received upvote score caused by surges of newcomers due to platform promotion [59], we further revealed the difference between user cohorts in OFCs. Particularly, we observed that the received upvote score of existing members was higher during the events than before and after the events, while an opposite trend existed for newcomers. One possible reason is that the language barrier identified in knowledge communication may also exist in entertainment communication [3], and newcomers may not be well guided to learn from the community members during the event.

Fourth, another salient contribution of this work is that we analyzed whether event-induced influxes may affect the correlation between user behaviors and future engagement. Our results showed that the user's current activeness positively predicted ($p < 0.001$) the future engagement, whereas the received upvote score seemed to be irrelevant ($p > 0.05$) to the future engagement whether it was during the event or not (from Table 6). This confirmed that the communication desire and community bonding mattered in OFCs [48]; however, it was inconsistent with the effect of community acceptance in community question-answering sites [18]. Table 6 also suggested that both the interaction diversity (out degree entropy) and the expressed sentiment during the events positively ($p < 0.05$) predicted the future engagement for all user cohorts, although the strength of correlation may vary for different cohorts in the ordinary period. This result might be supported by the spotlight effect [29, 30], that is, members may feel they are more important for OFCs when observing more users of the communities during events than in the ordinary period. Moreover, the impact of user interaction during an event on future engagement could vary across user cohorts. The received sentiment positively predicted the future participation of core fans but not returnees, while the in degree entropy positively predicted the future participation of returnees but not core fans. One possible reason is that negative responses hurt core fans who often feel the responsibility to promote their idols [68, 72], while diverse responses might help returnees find the value of OFCs. Table 6 also showed that the relative importance of daily activity was the highest in predicting future engagement for both returnee ($\beta = 0.1896$) and core fans ($\beta = 2.102$), while the interaction diversity ($\beta_{in\ degree\ entropy} = 0.0478, \beta_{out\ degree\ entropy} = 0.0715$) was more important than daily activity ($\beta_{daily\ activity} = 0.0257$) for newcomers. This may be because core fans felt resonated and returnees re-established their interest through information exchange activities [72], and newcomers were more likely to have a sense of community by interacting with diverse members [75]. The actual reasons as to why such differences existed across user cohorts and between different time periods (i.e., whether during the event or not) in OFCs could be explored in future qualitative research.

Overall, our findings uncovered new aspects of member dynamics in online music communities that were caused by the event-triggered influx of newcomers. Based on these insights, we propose several design implications for OFCs to take the opportunity to expand the fan base and manage potential negative impacts during the period with the influx of newcomers.

6.1 Implications for Online Fandom Communities

6.1.1 Encourage User Activity. Our result showed that member's activeness in OFCs (such as number of posts and comments) could be one reliable predictor of future engagement. Therefore, moderators could encourage members to engage in the community during the influx period if they want to enlarge the fan base. One possible method is to send a summarization of the recent posts [44, 82] via direct message to community members who once participated in the community discussion. Another potential approach is to design tasks (such as daily check-ins and weekly discussion topics) to promote member interest as well as to show the member's activeness ranking in a period (e.g., during the event). However, several issues should be considered to avoid the attrition of community members, which may lead them to quit the OFCs. First, moderators should control the frequency of sending community updates. Second, community members should have the autonomy to unsubscribe from the community notification.

6.1.2 Encourage Diverse Interactions. Our results showed that although the interaction could be more diverse during the influx period in contrast to the ordinary period due to massive newcomers joining, newcomers still interacted with narrower cohorts compared with existing members. However, the interaction between newcomers and existing members is important, since it is a foundation of the unity of the community [69]. Therefore, OFCs could develop mechanisms to encourage the interaction between newcomers and existing members during the influx period. For instance, the community moderator could establish a reputation system in the member profile as in other platforms (e.g., Stack Overflow), so that members could know the status (e.g., core fan, newcomer) of each other. The community could also directly recommend the posts from a group (e.g., existing members) to another group (e.g., newcomers), if members need [45]. Meanwhile, the community could employ the gamification mechanism, which gives more rewards (e.g., the Karma on the Reddit platform) for interacting with diverse user cohorts and vice versa. However, moderators should monitor the community member behavior regularly to explore the potential side effects of the new reward mechanism and carefully design the reward mechanism to decrease the negative effects. For example, community members may deliberately or unintentionally game the system by replying to low-quality content to multiple people for more reward [53, 85], which may lead to online harassment [7, 46, 52].

6.1.3 Strengthen Content Regulation. Our analysis suggested that during events, the sentiment of expressed and received content positively predicted members' future activity in OFCs. Therefore, moderators may need to monitor hate speech and other malicious content in online communities, especially when a sudden event happens. If too much negative sentiment is detected from members' activities, systems could offer interventions and give them reminders to encourage them to express themselves more positively. For instance, a system can be developed to assess the quality of the content (such as level of toxicity [1, 56] and the risk of triggering toxic content [2]) before a user submits the response, and provide some suggestions for users to improve the content quality if necessary [83]. It should be noted that the community norm and the tolerance of toxic content may vary across different OFCs [12], and researchers may need to tune the detection algorithm by co-designing with community members. Alternatively, researchers may apply NLP techniques to automatically propose high-quality responses (e.g., making the response more polite and empathetic) [76, 91]. However, it should be noted that members should have the autonomy to decide whether to accept the suggestions. Finally, OFCs could also consider filtering the received toxic comment, which helps to improve the sentiment of the received replies [40].

6.2 Limitations, Generalizability, and Future Work

The limitations of our work can be summarized as the following. First, we focused only on the music OFCs, while other communities that may attract an influx of newcomers due to events (e.g., the FIFA World Cup) were not in the scope of the work. In the future, we will generalize our analysis workflow to diverse communities where the influx of newcomers attracted by events exists. Second, although we carefully calibrated the dataset, some influx periods might exist where the causality is weak between newcomers and the corresponding events. Further actions can be taken to examine the discussed topics of the events in detail. Third, although our statistical analysis was successful in elaborating how members in distinct groups behaved differently along with the impact associated with the events, it may not be able to fully explain the reasons behind that. Moreover, the correlational analysis does not imply causality. To verify the findings, future qualitative works can be conducted to understand why members interact with others during dynamic periods and the reasons for their future engagement in OFCs, which could provide more practical insights.

We acknowledge that the COVID-19 pandemic may influence the format of events. For instance, we witnessed more online concerts in recent years compared to the pre-pandemic period, due to the challenges such as social distancing measures brought by the pandemic for celebrities to attract public attention [27]. On the other hand, some specific user behaviors may be impacted by COVID-19. For example, a recent study suggested that the pandemic could influence the preference for music listening [67]. However, since the direct trigger of the influx of newcomers (i.e., celebrity-related events regardless of the format and taste) are similar in essence no matter if it is before, during, or after the pandemic, our main findings could still be generalized. These include the difference between newcomers and existing members during the events, the impact of events on community members, and the correlation between user behavior and future engagement. Moreover, as the influx of newcomers driven by events would also frequently happen in the future, our suggestions for OFC regulation during the events (i.e., encouraging user activity, encouraging diverse interactions, and strengthening content regulation) could still be relevant to moderators of OFCs. While the specific impact of the pandemic on member engagement is out of the scope of this paper, future studies can apply our analysis workflow to explore this topic to complement our results. The resulting insights could be valuable for celebrities to decide on the released content (e.g., music and albums) during special timing, such as pandemics and natural disasters (e.g., earthquakes, hurricanes).

In this paper, we focused specifically on the music OFCs where the main motivation of community members is to curate, transform, and discuss content about celebrities, a typical type of OFCs. In these OFCs, celebrities were the discussion topic of the community, and social interactions only happened among fans. However, on other fan platforms such as TikTok and Twitter, it is becoming popular that celebrities may directly interact with fans and participate in the community discussion (e.g., commenting or sharing the fans-remixed videos) [72]. Such celebrity activities tend to attract public attention and stimulate information and opinion exchange among existing fans and newcomers. In this regard, they can be considered as "events" we studied, and our general findings may still apply despite the possibility that the direct interaction between fans and celebrities on these platforms might be higher than that in our selected OFCs. Besides, celebrities might consider adapting strategies proposed in this work (e.g., interacting with diverse cohorts and increasing interaction frequency with fans) to expand and strengthen their fan base. Celebrities may also need to regulate the community content when directly communicating with fans to avoid negative effects caused by newcomers as suggested by our results. We encourage researchers to generalize our workflow to other types of OFC platforms, customize the user cohorts (such as celebrities, existing members, and newcomers) according to the platform characteristics, and extract interaction features. In this way, future works can explore the interaction dynamics and understand the specific effect of celebrities' behavior on the fan base, which would be important for entertainment management agencies.

7 CONCLUSION

In this paper, we selected music OFCs as the focus of the study and conducted a series of quantitative analyses to explore the effects of the event-induced sudden influxes of newcomers on OFCs from the perspectives of discussion topic, community structure and user engagement. We found that during the influx period, newcomers were more likely to express hate speech and negative sentiment, praise less celebrity-related content, and interacted with narrower cohorts than existing members. The interaction between users appeared to be more diverse and evenly distributed with surges of newcomers in OFCs compared with that during the ordinary period. Although existing members tended to receive more upvotes during the events than both before and after the events, newcomers showed an opposite direction. Furthermore, users' activeness, expressed sentiment, and the interaction diversity during periods of influx were positively correlated with their future levels of engagement. Based on these insights, we proposed several design opportunities for OFCs to utilize the chance to expand the fan base and manage potential negative consequences caused by the influx of newcomers. This work extended the empirical understanding of fan behaviors and future engagement in the dynamic periods, and our insights would benefit the healthy development of OFCs when such an influx occurs. Future works could further explore the effects of direct interaction between celebrities and fans and special timing (e.g., pandemic) on members in OFCs.

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