Viral Design: User Concepts of Virality on the Niche Social Media Site, Dribbble

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ABSTRACT

Virality is a much-studied topic on popular social media sites, but has been rarely explored on niche sites. Dribbble is a niche social networking site for artists and designers with over 600,000 users. Using a mixed-method approach, we explore virality from a user-centric perspective. Interviews confirm that viral-like events do exist on Dribbble. Through interviews we identify the measures and possible driving factors of viral-like events. While what spreads is different than on other platforms, our work suggests that the measures and mechanics that drive these events are similar. These similarities reflect fundamental human behavior underlying social phenomenon across different platforms. Our results are supported by regression modeling using variables identified by our informants. Smaller sites like Dribbble are rarely studied, so our work contributes to social media studies, particularly using mixed methods approaches, and to the body of research around information diffusion and viral events.

CCS CONCEPTS

• **Information systems**→ World Wide Web→ Web applications→ Social networks • **Information systems**→ World Wide Web→ Information systems ~Social networking sites

KEYWORDS

Virality, social Media, Dribbble, mixed-methods

SMSociety '18, July 18–20, 2018, Copenhagen, Denmark

ACM ISBN 978-1-4503-6334-1/18/07…$15.00
https://doi.org/10.1145/3217804.3217901

1 INTRODUCTION

Nahon and Hemsley define virality as a "social information flow process where many people simultaneously forward a specific information item, over a short period of time, within their social networks, and where the message spreads beyond their own [social] networks to different, often distant networks, resulting in a sharp acceleration in the number of people who are exposed to the message" [17]. Their definition reflects a large body of literature studying virality on sites like YouTube, Facebook, Twitter and email. In other words, our understanding of the phenomenon of viral events is based primarily on the largest sites or communication channels. Despite this, a 'non-exhaustive' list of social media sites on Wikipedia contains 206 'notable, well-known sites' [31]. This suggests an opportunity around examining 'virality' on social media niche sites in an effort to understand if the phenomenon is similar or different depending on the scale or focus of the site. Similarities would suggest that the phenomenon reflects fundamental human behavior, while differences might suggest that the nature of virality depends on characteristics related to the sites.

In our work on studying Dribbble.com, a social network site created in 2009 for designers and artists to share and get feedback on their work, we find that while Dribbble, lacks features that allow for the sharing and re-sharing of user generated content, our informants report conceiving of virality in similar ways to that found in the body of literature around viral events.

In this study we use Becker's concept of an 'art world' [3], networks of actors whose cooperative work produces art, to understand the creative environment of Dribbble, and we use Nahon and Hemsley's [17] concept of viral events as a point of comparison for viral-like events on Dribbble. We also use a sequential exploratory mixed-method approach [8] to understand if something like virality takes place on Dribbble and if so, how does it manifest and what are its driving factors. We use interview data from 28 informants to understand how Dribbble users use the site, how they think about virality on the site and what factors might drive virality. With the factors related to viral events identified by our informants and the literature, we collected over 400,000 user profiles and more than 700,000 artistic images and associated metadata from Dribbble's public Application Programming Interface (API), to develop variables for a set of regression models to examine the relationships between various factors and measures of viral-like events on Dribbble.

We find that while user designs and art are not re-shared, our interview informants do tend to apply the concept of virality to art that receives a high number of views —particularly when this happens suddenly. They also suggest a number of factors that drive these viral-like events, such as the number of followers one has. Our regression models suggest that factors identified by our informants are similar to those found in the literature around viral events, and that those factors are related to the number of views an artwork receives. These findings allow us to discuss the similarities and differences of viral-like events on Dribbble compared to other sites, like Twitter. Data from our informants also suggest that what spreads on Dribbble is not specific works of art or design, but rather, users 'borrow' elements from other's works, such as color palettes, design solutions and other stylistic choices, which they employ in their own works. These design flows can turn into 'trends' on the site, and such trends can be driven by larger design industry trends.

Our work contributes to our understanding of content diffusion and viral events by identifying common patterns on large and small social network sites that provide some insights into how emergent human behavior is played out through different affordances on different kinds of social media sites. Our hope is that this work informs work on other niche social media platforms, such as on academic social network sites and music sites, which we believe will broaden our understanding of the social behaviors that underlie viral events.

2 LITERATURE

2.1 The Dribbble Art World

We adopt Becker's [3] concept of an 'art world' to understand and explore Dribbble. Art worlds are made up of a network of actors whose cooperative and collective activities result in the creation of works of art. In other words, an art world is where the mundane work of creating art is done [3]. Conventions arise out of the interactions and activities of the actors that inform artistic production, mediate cooperation and define what qualifies as 'good art' within the art world. Becker notes that art worlds have no boundaries, rather they are overlapping networks where artists are embedded with other actors who support the work of creating art. For example, the technical support agent at Adobe who answers an artist's question about Adobe Illustrator is part of the art world, as are those who view, give feedback and appreciate the art.

What constitutes 'good art' is defined by those in the art world. For this study, the concept of good art is an important one since it might be related to or overlap with viral-like phenomenon. That is, we would expect things that are considered good art, are more likely to become viral than things that are not. Nahon and Hemsley [17] have theorized that social norms are re-instantiated and transformed through the process of viral diffusion. Thus, one explanation for the evolution of art on a site like Dribbble is that as artistic innovations diffuse through art worlds, they may change the conventions (roughly equivalent to 'social norms') that inform artistic production, mediate cooperation, and define and redefine what qualifies as good art and who are good artists [3]. Indeed, Becker has called for studies of diffusion in art worlds to understand both how conventions change over time as well as to understand how art evolves. By focusing on Dribbble, we are examining a subset of an art world, one where viral-like events might happen. Note that while Dribbble is primarily thought of as a site for designers, we will generally use the term 'art' since we are borrowing Becker's conception of an art world.

Dribbble is a social networking site [4] whose terminology is based on basketball terms, and functions as the online part of an art world by enabling "players" (users), to form networks through follower and following relationships. The follower network on Dribbble can be thought of as a subset of an art world, one where diffusion might happen among the networked actors. Like other sites, the distribution of followers on Dribbble is highly skewed. That is, a small set of players have thousands of followers, while the majority of players have tens or hundreds. High numbers of followers may signal who the actors in the art world collectively consider good artists.

When a player clicks on the thumbnail of another player's "shot" (art or design work), it opens a new page with a larger version of the shot. Each visit counts as a "view" for the shot, and the numbers of views is displayed on the shot's page. Players can also "like" and comment on this page. Views, likes and comments may all be signals of what players collectively determine what counts as good art in the Dribbble art world. Players also signal enthusiasm for other's shots by posting "rebounds" (i.e., response art – art that they make in response to other people's art; generally, a variation of an original art). When a shot receives more than one rebound, it is referred to as a "playoff", and is featured on the Playoffs page. Dribbble also has dedicated pages for shots that are 'popular', 'recent', and 'debuts', where debuts are for the first shot posted by those who become a player after receiving an invite.[1]

There are few studies that look at art related social media sites, much less with a specific focus on viral events that occur on them. One study looking at Dribbble used a database of U.S. baby names [2] and found that male designers tended to have more success at getting views and likes, and that while women had fewer ties in the site's social network, they had more cohesive social networks than men [27]. Similarly, a quantitative study of Behance, another online social network site for designers, found that males tended to have more followers and that grayscale images tended to receive less attention [14]. Salah et al. [21] looked at the relationship between network clusters and artistic subcategories on DeviantArt, a site for a broad range of artists, and found that clusters of users on the site tended to form around production techniques, not types of art. None of the above studies focuses on viral, or viral-like events on an art site. However, Salah and Salah [20] have explored the diffusion of art innovations on DeviantArt. They started by selecting artwork that was posted as a "resource", or a downloadable stock image, which are intended to be mashed up or embedded in other artists' work. When other artists use these stock images in their own work, Salah and Salah consider this a kind of diffusion of technique. We note that their work starts with content intended by the artists to be used by other artists, and so what Salah and Salah are looking at is not the emergent crowd driven event we typically associate with a viral event. Rather, it is somewhat more like a meme [22] than a viral event.[2] Also, all of the work above only uses quantitative analysis, and so does not include the experience and views of the site's users.

2.2 The Viral Phenomenon

Nahon and Hemsley suggest that, "virality is a consequence of dialogue and tension between many forces. The main tension occurs between the emergent sharing patterns of users (usually constituted through bottom-up processes) and the control mechanisms exerted on information flows (usually driven by top-down processes, e.g., network gatekeeping and social and network structures)" [17]. Within the audience, the bottom-up process emerges out of patterns, human attention and social influence. The top-down process is largely the result of actors whose position within networks allows them disproportionate influence over the flow of content in networks. The concept of a "dialogue" captures the idea that virality happens when you have both the bottom-up and top-down processes working together to bring content to the attention of the audience by sharing it into their own networks. The "tension" exists when the two are not working in tandem and the content fails to go viral. For example, a news outlet posts a story that the audience views, but does not share into their own networks. Alternately, someone in the crowd shares new content that is perhaps shared by their immediate followers, but fails to reach the wider audience that those at the top, too, have access to.

Thus, even when those in influential positions wish for something to go viral, without the crowd spreading, sharing or copying content, such that their own followers see it, content will stay obscure. The actors in the crowd, as well as at the top, have agency in the viral process. But without well connected actors at the top, content tends not to reach very large audiences. In our social networks, it is the hubs, or, as Nahon and Hemsley call them, "network gatekeepers," who are in a position to bridge dispirited audiences and propel content further than it would otherwise go. Importantly, network gatekeepers may be people, or organizations, but they might also be the algorithms that select the content we see on social media sites.

Dribbble, like many social networking sites, has typical users who we might think of as the crowd, as well as highly influential actors with thousands of followers. Thus, it has the basics of the 'bottom' and 'top' that Nahon and Hemsley discuss. We also assume that some algorithm influences what players see when they login, but that the players still have agency when choosing which shots to view and interact with in different ways. Thus, our first research question is: *RQ1: Does something like virality exist on the niche social media site Dribbble?*

As mentioned above, there is some evidence that users on DeviantArt do adopt the style and technique of other users into their own work [20]. It is then reasonable to assume that the diffusion of stylistic characteristics might exist on Dribbble too. Thus, our next research question is: *RQ2: If viral-like events do happen on Dribbble, what is diffusing in the Dribbble art world?*

Dribbble does not have a share or retweet button, so players cannot share the work of others directly into their own networks. Conceptually, Dribbble is more like YouTube in that messages themselves do not spread. On YouTube, the concept of virality is that users share links to a video, which is embedded on the poster's channel page [6]. So what is being shared is actually a Universal Record Locator (URL), and studies [18] typically use the number of views a video gets as a measure of virality. Thus, the number of views a shot gets could be a measure of a viral-like event.

In terms of the factors that drive viral events, we turn first to the concept of 'top-down' and 'bottom-up' processes

[1] Dribbble has an invite-only model such that anyone can join the site, but only those who receive an invite from another player are allowed to post shots. Dribbble periodically supplies selected players with a small set of invites to hand out. The stated goal of this policy is to ensure a high quality of content and interaction.

[2] For a detailed discussion of the differences between a meme and viral event, see the end of chapter 2 in Nahon and Hemsley, 2013. Also see Shifman, 2013.

and find that Nahon and Hemsley's concept of network gatekeepers is heavily influenced by an understanding of networks. For Nahon and Hemsley, gatekeepers are "people, collectives, companies, or governments that, as a result of their location in a network, can promote or suppress the movement of information from one part of a network to another" [17]. By 'location in the network' they mean that because of the high number of links or followers that gatekeepers have, they can exert some level of control over the flow of information. Indeed, an actors' number of followers has consistently been found to be related to how viral their content goes [13, 15, 25, 30].

Other factors from the literature examining big data inquiries include network effects like: to whom one is connected [9, 29], who sent the message [15], and how frequently two actors interact [12]. Research has also shown that content that is novel [19, 28], emotional [23], or resonates with people [1], is more likely to go viral. Other large scale work has shown that the user's account age [16], the number of tweets users have posted, and the number of their tweets that have been favorited are also related to how often they are retweeted [25]. Tweets with hashtags, URLs and @mentions all tend to be retweeted more than those without such textual features [24]. With these factors in mind we expect that if viral-like events happen on Dribbble we ought to find that similar factors are at work. Thus, we seek to identify the factors that are driving these viral events. Our final research question is: *RQ3: What are the measures and factors of viral-like events on Dribbble?*

3 METHODS AND FINDINGS

In this study, we adopt a sequential exploratory mixed-method approach [8]. We start with qualitative data collection and analysis to explore our phenomenon through semi-structured interviews with Dribbble's members. We use data from our informants to answer our first and second research questions and to inform the variable selection for regression models. We then use the models to answer the third research question, which focuses on identifying factors that drive these events. As such, we present the methods and findings of the qualitative interview work before presenting the methods and findings of the quantitative regression modeling efforts. In the results of the quantitative work we introduce hypotheses that drive model development.

3.1 Player Interviews

Recruitment of interviewees was conducted by email. Dribbble does not have a public internal messaging system, though some players opt to have a "hire me" button. In our consideration of how to conduct our work ethically, we opted not to use the "hire me" button because even though we planned to offer a $20 Amazon Gift Card for an hour interview, we felt that using the button would be misleading. However, slightly less than 5% of users include an email address on their profile page. To arrive at this number, and to collect email addresses to contact users, we used Dribbble's application programming interface (API) to collect over 400,000 [3] user profiles. Of those, 50,117 included a user specified location that we could use with a geocoder to determine a location. The most users were in the U.S.A. (12,816), followed by China (4,761), the UK (3,348), India (3,208) and Russia (1,847). Figure 1 shows the global distribution of users, where counties with more users are darker.

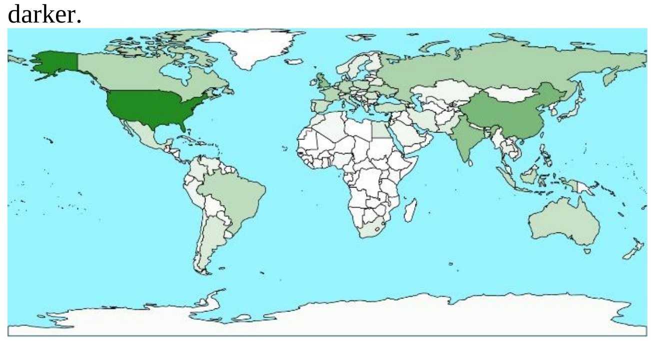

Figure 1: World map showing user-listed country locations.

For our interviews, we programmatically mined user profiles for those who listed English as their language and included an email address. Audio-only interviews took place on Adobe Connect, a web conferencing tool, and were recorded for later transcription. Note that our methods and interview protocol were vetted and cleared by our institution's internal ethics review board.

3.2 Interview results

In total, we conducted 28 interviews (19 males and 9 female) with informants between the ages of 18 and 38 (mean = 26.4). Most of our participants have been using the platform for more than three years. Our informants describe themselves as UI/UX or product designers, graphic designers, illustrators, or motion graphic designers.

Without exception, all of our respondents indicated that they used the platform for artistic and creative inspiration. Subsets indicated that they also used the platform to get feedback on their work, promote themselves, maintain a public presence and portfolio, find jobs or other designers to work with, or to keep up with design industry trends. When asked about other platforms they posted art (designs) on, our participants listed, in order of frequency, Behance, Instagram, Facebook, Twitter, DeviantArt, Pinterest and Vimeo. Players indicated they posted shots to gain exposure for their work, get feedback, receive validation and to

[3] The site's 'About' page suggests that the site has around 600,000 users. Our profile collection was accomplished through a snowball method where we started with a few active users' profile IDs, which we manually gathered from URLs to their profile pages. Using these as seeds, we gathered all of their followers and their followers' followers until no more new names were added. This essentially gave us the websites' largest network component.

challenge themselves (e.g., by participating in challenges or rebounds).

Dribbble allows users to view, like, comment on, rebound and save into buckets, others shots. Several informants indicated that they would like, comment on, or save into buckets shots that they thought were ‘good’. Some informants said that they might also like or comment on other’s work as a sign of support and that comments were also used to ask questions or provide feedback. In our conversations with them, we learned that many saw a hierarchy in the meaning of these features; rebounds to one's shots might be thought of as the highest compliment, followed by comments and finally likes. For example, Informant 8 noted of rebounds that, “I think it’s a way of complimenting the original artist.” Thus, we find that Dribbble provides a number of indicators of good art, which is a key element of Becker’s art world concept.

When probed about what constituted good art, our informants indicated that work that inspired them, solved design problems in a novel way, evoked emotion, conveyed meaning, or were visually appealing could all constitute good art. Informant 14 also said that “anything that drives a conversation, drives a sort of topic that you would not have considered otherwise can be considered as good art,” and Informant 20 said that good art is “something that like makes people think and makes people think of new ideas and inspires people.” In general, our informants felt that good art tended to get more attention and, when talking about getting views and followers, Informant 26 said that “if your work is good it will build audience organically.”

In discussions with our informants, they frequently mentioned the idea of design trends on Dribbble, where many people posted shots with a similar look and players were inspired or influenced by others. One informant referred to this as a design “echo chamber”. Our informants also indicated that trends could originate outside of Dribbble. For example, when Apple released its Touch Bar, designers across Dribbble quickly posted their own versions of Touch Bar icons and mimicked each other. Informant 2 told us that their lead designer “designed a Touch Bar for Dribble right away and then we posted it on Dribble and then we got lot of likes because at that time everybody was interested in that and everybody was looking for it, so we got lot of likes and exposure.” But design trends can also be local to Dribbble, such as when Dribbble noted on their blog that a wave of purple shots had washed over their Popular Shots page [10]. Thus, the answer to the first research question is that yes, something like virality exists on Dribbble, and one way it manifests is in the form of design trends.

One of the most important uses of Dribbble by our informants was to seek out inspiration and keep up with the trends. For example Informant 6’s comment: “It usually happens early in the morning when I come to the office and see quickly okay what’s happening in the design community, what’s new.” While players indicated they did not copy the shots of others, the majority of our informants indicated that their own work was influenced by other players. According to Informant 4: “I always end up with my own personally unique idea that got inspired by some users.” They described adopting into their own work design elements like color palettes, line styles, textures, fonts and so on. Places they found such stylistic inspiration on Dribbble included their own landing page, which aggregated recent shots from those they followed; the Popular Shots page, which appeared to order shots by a proprietary algorithm; or by using the site’s search tools. The search tools allow players to find shots by user-supplied keywords or auto-tagged colors. Thus, players may have a design problem in mind, or a set of requirements from a client, and after browsing Dribbble, they would borrow, for example, a color pallet or a line style that inspires them and incorporate it into their own work. Thus, in answer to research Question 2, what seems to spread on Dribbble are stylistic elements of shots.

When talking about popular shots, Informant 5, similar to others, said: “The thing that is the top or get the most likes and views … I'd call it a viral.” Several of our informants also noted that having their shot featured on the Popular Shots page was also a sign of virality since that seemed to result in shots getting even more views. The number of views, then, could be seen as a measure of virality. Some informants also saw the numbers of likes as an indicator of popularity or virality. For example, Informant 23 reported: “With a big amount of likes and then suddenly the picture is on everyone’s radar and then it’s like it [the shot] will be picked up by a lot of other people.” Talking about virality, Informant 26 said, “…in terms of what gets the better engagement, the most amount of likes, is…” Another measure of virality is numbers of comments; Informant 19 suggested that viral was “the work that are the most viewed and most comments,” and Informant 18 explained “If it [a shot] is that good, I get a lot of comments and a lot of likes that means your design succeeds.” Thus, part of our answer for research question 3 is that the numbers of views, likes and comments may all be used to measure a viral-like event.

When asked about the factors that seemed to drive these viral-like events, some thought that shots going viral was driven by luck, but most felt that those with more followers would get more views and likes just because their shots would show up in more people’s feeds. Specifically, Informant 14 explained: “In order for your work to get viral, you need to have a lot of followers and you need to have a lot of exposure.” Informant 24 echoed this: “So the larger followers they will see your work whenever you post it up and you can manufacture likes and use that way.” When asked about the popular designers, some of our informants explained: “They just have a lot of followers and a lot of people comment on their images” (Informant 22), and “I mean if the things they post get a lot of likes” (Informant 20).

Thus, our informants have identified some of the potential factors that might drive viral events. As such, we propose the first set of hypotheses for our regression models to see if there is a relationship between the number of followers and potential measures of viral-like events on Dribbble:

H1a: Numbers of followers are positively related to number of views.
H1b: Numbers of followers are positively related to number of likes.
H1c: Numbers of followers are positively related to number of comments.

Similar to Twitter, our informants saw the uses of hashtags as a way to support searching and increasing exposure. For example, Informant 26 explained: "Then there's also the, you would call them hashtags or tags that you would put on your design work. So, depending on what I'm working, I'm going to put relevant tags so that people searching those later, so say I created a 404 page and I tagged it as 404 if someone else is looking for inspiration like that and they're at 404 my piece might show up or should technically show up." We pose the following hypothesis to test if hashtags are one of the drivers of viral events:

H2a: Numbers of hashtags are positively related to number of views.
H2b: Numbers of hashtags are positively related to number of likes.
H2c: Numbers of hashtags are positively related to number of comments.

Native to Dribbble, the platform offers a saving mechanism, namely buckets. Some of our informants explained using bucket as a way to show appreciation, saying: "It [bucket] almost gives you the self-gratification of like hey this person likes my work and then they added it, like they took the effort to favorite it and then put it into their bucket stating that they liked this as inspiration" (Informant 16). We propose the last set of hypotheses, to see if the numbers of buckets a shot is in could be a driver of viral events on Dribbble:

H2a: Numbers of buckets are positively related to number of views.
H2b: Numbers of buckets are positively related to number of likes.
H2c: Numbers of buckets are positively related to number of comments.

So in terms of factors that could be drivers of viral-like events on Dribbble (research question 3), the number of followers, hashtags and buckets seems to be the main factors that informants could identify.

Other, less easily measurable factors, also came up in discussions. A few informants mentioned that Dribbble's algorithms seemed to prioritize some shots over others in the order of appearance on the Popular Shots page. A couple of informants also clued us in about how to game the system by posting links to their shots on other sites to bump up the number of views their shots got. The idea being that this behavior might result in their shot getting featured on the Popular Shots page. Informants also linked the idea of virality to exposure, indicating that having your shot go viral could bring you a lot of attention in terms of likes, comments and new followers.

3.3 Regression Modeling

Data for the regression models was drawn from Dribbble's API. In addition to the profile information described above, we collected metadata of more than 700,000 shots.

We developed linear regression models using various measures of virality as informed by the interview data, namely number of views, likes and comments. Our independent variables include metadata about the shot or the player who posted it. These include the number of followers of the player, the number of hashtags listed in the shot's description text, the age of the shot, the number of buckets a shot is in, where a bucket is a grouping mechanism for players to group their own or other shots into collections. The shots are drawn from 100 randomly selected players, stratified by their number of shots. The numbers of shots per user ranges from 30 to 688 with an average of 83.18. In total, we use 8,318 shots for our models.

To satisfy the assumptions of linear regression (dependent and independent variables are linearly related, and errors are independently and normally distributed with constant variance), we calculate and note that Variance Inflation Factor (VIF) scores of the independent variables range from 1.0 to 1.2, indicating that our models do not suffer from multicollinearity. As is typical [11], we use plots for regression diagnostics, all of which are available upon request.

Accordingly, we constructed three regression models on the virality measures suggested by our informants: number of views, likes and comments. The independent variables are similar for all models. The variables are listed below.

VIEWS, LIKES and *COMMENTS*: Continuous dependent variable for model 1, 2 and 3, respectively.
FOLLOWERS: Continuous variable representing the number of followers a user has (H1).
TAGS: Continuous variable representing shot's number of hashtags (H2).
BUCKETS: Continuous variable representing the number of buckets a shot has been added to (H3).
AGE: This control variable is a continuous variable representing the age of a shot in days.

3.4 Regression Results

We use regression modeling to see if the factors identified by our informants as being drivers of viral-like events are indeed related to different possible measures of viral like events.

Our first regression model using the number of views as the dependent variable confirms that followers are related to views, but as noted above, we include other variables as well. The results are presented in Table 1 where we report the estimated coefficients, confidence interval, standard error, t-test statistic and p-value. The R-Squared of 0.64 indicates that our predictors explain the variation in the outcome sufficiently well. All predictors are statistically significant.

The estimated coefficient of FOLLOWERS suggests that one more follower increases the number of views by 0.11, while holding other variables constant. The TAGS estimated coefficient suggests that adding one more hashtag increases the number of views by 35.81, and the estimated coefficient of BUCKETS suggests that being in one more bucket increases the number of views by 202.89. Thus, if we accept the number of views as one of the virality measures, H1a, H1b and H1c are all supported.

Surprisingly, the estimated coefficient of shot age suggests shots a day older decreases the number of views by 0.1, suggesting the number of views shots receive decreases over time. Thus, the number of views a shot gets may spike up when the shot is new, and then gradually decline over time, which is similar to how viral events are characterized on other platforms [5, 7, 13, 28]. Figure 2 shows the scaled (0 to 1 for comparison) hourly view rate for a random selection of 500 shots in blue on the left, with the average for a given hour after posting highlighted in red. On the right, figure 2 shows what Nahon and Hemsley [17] would describe as more (dashed line) and less (solid line) of socially shared content, such that the dashed line would be considered more viral and the solid line would be more promotional.

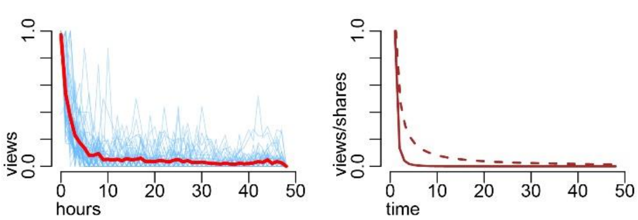

Figure 2: Left, hourly view, from initial posting, for 500 random shots. Right, the difference between the number of views for promoted content (solid line) vs. viral, socially shared content (dashed line).

Table 1: Regression model on numbers of views. We report estimated coefficients (EST), confidence intervals (LWR, UPR), standard errors (SE), t-test statistics (T-VAL) and p-values (P-VAL).

VIEWS =	EST	[LWR, UPR]	SE	T-VAL, P-VAL
Intercept	103.96	[-14.02, 221.93]	60.18	1.73, 0.08
FOLLOWERS	0.11	[0.09, 0.14]	0.01	9.23, <0.01
TAGS	35.81	[25.24, 46.38]	5.39	6.64, <0.01
BUCKETS	202.89	[199.34, 206.44]	1.81	112.04, <0.01
AGE	-0.10	[-0.16, -0.13]	0.03	-2.92, <0.01

Residual standard error: 1968 on 8313 degrees of freedom
Multiple R-squared: 0.6438, Adjusted R-squared: 0.6436
F-statistic: 3756 on 4 and 8313 DF, p-value: < 2.2e-16

For the number of likes, our second model (Table 2) shows that our predictors explain the variation in LIKES very well with the R-Squared of 0.78.

The estimated coefficient of FOLLOWERS suggests that one more follower increases the number of likes by 0.02, while holding other variables constant. The TAGS estimated coefficient suggests that adding one more hashtag decreases the number of likes by 0.23, and the estimated coefficient of BUCKETS suggests that being in one more bucket increases the number of likes by 3.81. Again, if we accept numbers of likes as another measure of virality, only H2a and H2c are supported while H2b is not.

Similar to VIEWS, the estimated coefficient of shot age suggests shots a day older decreases the number of views by 0.02.

Table 2: Regression model on numbers of likes.

LIKES =	EST	[LWR, UPR]	SE	T-VAL, P-VAL
Intercept	30.17	[28.08, 32.27]	1.07	28.24, <0.01
FOLLOWERS	0.02	[0.02, 0.02]	0.00	78.76, <0.01
TAGS	-0.23	[-0.42, -0.05]	0.10	-2.44, <0.01
BUCKETS	3.81	[3.75, 3.87]	0.03	118.47, <0.01
AGE	-0.02	[-0.02, -0.02]	0.00	-31.63, <0.01

Residual standard error: 34.93 on 8313 degrees of freedom
Multiple R-squared: 0.778, Adjusted R-squared: 0.7779
F-statistic: 7282 on 4 and 8313 DF, p-value: < 2.2e-16

Our last model, with the number of comments as the dependent variable, is presented in Table 3. This shows that our predictors explain the variation in the numbers of comments well with the R-Squared of 0.44.

The estimated coefficient of FOLLOWERS suggests that one more follower increases the number of comments by no greater than 0.01, while holding other variables constant. The TAGS estimated coefficient suggests that adding one more hashtag decreases the number of views by 0.03, and the estimated coefficient of BUCKETS suggests that being in one more bucket increases the number of views by 0.12. Again, if we accept numbers of comments as another measure of the virality, only H2a and H2c are supported while H2b is not.

Contrary to the other models, the estimated coefficient of shot age suggests shots a day older increases the number of views by no greater than 0.01.

Table 3: Regression model on numbers of comments.

COMMENTS =	EST	[LWR, UPR]	SE	T-VAL, P-VAL
Intercept	0.26	[-0.03, 0.55]	015	1.76,0.08
FOLLOWERS	0.00	[0.00, 0.00]	0.00	63.15, <0.01
TAGS	-0.03	[-0.06, -0.01]	0.01	-2.58, <0.01
BUCKETS	0.12	[0.11, 0.13]	0.00	26.76, <0.01
AGE	0.00	[0.00, 0.00]	0.00	3.53, <0.01
Residual standard error: 4.839 on 8313 degrees of freedom Multiple R-squared: 0.4421, Adjusted R-squared: 0.4419 F-statistic: 1647 on 4 and 8313 DF, p-value: < 2.2e-16				

In order to compare the effects of the variables driving virality, we also report the standardized coefficients (betas) for all models in Table 4. Amongst our hypothesized variables, the most important variable driving the number of views and likes is BUCKETS, but it is FOLLOWERS for the number of comments. The variable with smallest effect is similar across the three models, TAGS.

Table 4: Standardized coefficients of the three regression models.

Beta	VIEWS	LIKES	COMMENTS
FOLLOWERS	0.07	0.44	0.55
TAGS	0.05	-0.01	-0.02
BUCKETS	0.77	0.65	0.23
AGE	-0.02	-0.17	0.02

4 DISCUSSION

An art world is a place where the mundane work of making art gets done [3]. Dribbble is such a place, but, as is true in other creative web venues [26], players take on many different roles in this creative effort. Players act as artists, certainly, but also as audience, feedback providers, tool recommenders, and supporters to others. By following others, they also play a role elevating the talented from the rest in order to prove that “artists have a special gift” that cannot be fully understood outside of judging the artwork produced in the art world [3]. As audience members, players collectively signal what constitutes ‘good art’ within the art world by viewing, liking, commenting and rebounding. Through their comments, players act as supporters, providers of feedback and tool recommenders. In other words, the art world network of players on the site is constituted by actors who may take on many different roles at different times.

Our work suggests good art, as judged by the players on Dribbble, may get more attention in terms of likes and players gaining new followers. Often what is considered ‘good’ is what solves design problems or otherwise provides inspiration to other players. Our informants consistently indicated that finding inspiration was one of the most important uses of Dribbble. When players have design problems, need to get ideas for a project, or are just looking for a challenge, they browse through the shots of other players. While players were quick to say they did not steal the work of others, they described adopting elements of style, like color palettes or line work, from the shots of others and using them in their own work. Some even created buckets of themed shots for inspiration, and others described mixing elements of a set of shots together into a new shot.

That is, the shots of some players become useful resources whose elements become embedded in the art work of other players. In this way, shots can be co-created, and, as Becker suggests, emerge out of the collective activities of the network of actors in the art world. These elements of design are what is diffusing in the Dribbble art world. Of course, as on other platforms, most things do not diffuse far from the source [17]. Thus, we suspect that few shots inspire enough other players that we could consider then viral-like events. So while they might influence the art work of a few players, they do not simultaneously reach many actors in a short period of time as a result of social processes. And yet, our informants note that design trends do sweep through Dribbble. As described by our informants, the process can look like an echo chamber where a player’s work might inspire others, whose work further inspires others until, for example, enough players are all influencing each other such that Dribbble’s ‘popular page’ is filled with shots dominated by the color purple [10].

This diffusion of stylistic choices could be one explanation for the evolution of art in an art world. That is, as players see good art while seeking inspiration, they may view, like comment and include those shots in buckets. As a shot gets more attention, the site’s algorithms may prioritize it such that it gets even more views and, possibly inspires others. In a relatively short period of time, this could lead to a trend on the site.

To demonstrate how diffusion may alter conventions in the art world, we propose the following scenario: a trend setting shot was created with a new software package that creates a new visual effect. As the shot becomes popular, other players may ask how it was created, which leads the player of the original shot to write comments about the new tool. This could lead others to start using the tool, and posting their new shots as rebounds to the original shot. By altering the preferred tool set, the conventions around how shots are made have evolved to include the new tool.

Additionally, as new players post new shots made with the tool, a new convention around what is considered good might emerge. Certainly this is speculation, but falls well within the description of how viral events can change norms put forth by Nahon and Hemsley [17] and discussed above.

Our work suggests that some of the same mechanics that drive viral-like events on Dribbble are similar to factors that drive viral events on other sites. For example, we have shown that potential measures of viral-like events, such as the number of views a shot gets, are significantly related to the number of followers of the player who posted it. This is similar to studies showing a relationship between the followers someone has and the number of retweets they get [24, 25]. Just like viral events on Twitter or YouTube are said to be partly driven by network gatekeepers who exercise disproportionate control over the flow of information, players on Dribbble tell us that shots that reach the popular page get more views and that Dribbble's algorithms probably play a role in the number of views a shot gets. We can view both the popular page and the site's algorithms as performing the role of network gatekeepers in Nahon and Hemsley's view of viral events [17]. That is, some actors (technological ones in Dribbble's case) can select and promote messages such that they reach a much larger audience than they would otherwise. Without these network gatekeepers, users may find their messages remaining obscure because they lack the connections for the messages to spread much farther than their own followers.

Nahon and Hemsley claim that "viral events are not new" [17]. They note that on December 1st, 1955, Rosa Parks was arrested in Montgomery, Alabama, for not giving up her seat to a white person on a segregated bus, and that the news spread via phones, hand-bills and word of mouth, such that within three days, over 40,000 African Americans had joined a boycott of the bus system. They say that what is new is that with social media "a viral video, a news story, or a photo can reach 40,000 people in hours, or even minutes, instead of days" [17]. We suggest that what we see as viral-like events on Dribbble reflects a basic human phenomenon that has always existed and is manifested in different ways depending on the context (sharing art vs. sharing news) and the mechanisms available to people (share and retweet buttons or not). Before the Internet, phones, hand-bills and word of mouth spread news through crowds; on Twitter 280 characters can be retweeted by thousands. In turn, on Dribbble many people viewing the same art work(s) may adopt elements of them into their own work, to the point that echo chambers, or design trends emerge. But certainly design trends have always diffused as artists became inspired by other artists by visiting museums, art galleries, reading magazines or other venues. Perhaps Dribbble speeds up this process.

Dribbble's context, a place to share and feature art and design work, necessarily means that what spreads and how that happens will be different than, for example, a video on YouTube that goes viral. But some aspects seem similar, like the underlying factors that drive it (e.g., network gatekeepers, number of followers), as well as how viral events tend to spike up and then die down over time.

In future work, we intend to do more detailed comparisons across other niche sites, like Research Gate and Musical.ly, to tease out the similarities and differences across multiple platforms in an effort to isolate what is platform specific and what are the fundamental human behaviors that drive viral events.

5 CONCLUSION

This work examines the concept of virality in the Dribbble art world using a mixed-method approach. We began with the semi-structured interviews with the platform's users in order to understand the larger context of Dribbble's art world, giving us a user's perspective of the site and of how viral-like events work there. Using data from the interviews, we identified the constructs for measuring virality, as well as some possible driving factors. We then used linear regression models to confirm the relationships amongst variables. We discuss the form that virality appears to take on Dribbble, including the role of top-down and bottom-up forces. Specifically, we suggest the top-down forces are driven by network gatekeepers in the form of site's algorithms, and bottom-up forces are evidenced by the emergence of an echo chamber, as well as the popular page where the crowd collectively endorses shots to get featured. This work serves as a bridge connecting an extensive body of literature concerning virality in social networks to a significantly smaller body of work looking at niche art sites, like Dribbble. Our work confirms that the mechanics that drive viral-like events on Dribbble are similar to factors found elsewhere such as number of followers and the practices of network gatekeeping.

While this work is not specifically focused on the evolution of art in art worlds, our work does provide some support for the idea that such evolution could be driven by viral-like events in art worlds.

Finally, we note that this work has been approved by our institutional review board. The interview data has been stored under a password protected drive and the only reference to informants is done using an id number. Data gathered from the site has been aggregated such that no users' screen names or data are revealed in this paper.

ACKNOWLEDGMENTS

Seed funding for this project came from the Center for Computational and Data Sciences at School of Information Studies at Syracuse University. We would like to thank Suchitra Deekshitula, Jennifer Sonne and Yihan Yu for their help on this project.

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