A social network analysis of the online fashion community surrounding Poshmark.com

Rema Salman
School of Computer Science, Physics and Mathematics, Linnaeus University, Sweden
rs223bc@student.lnu.se

Madelene Logren
School of Computer Science, Physics and Mathematics, Linnaeus University, Sweden
ml225pj@student.lnu.se

Abstract: There is an abundance of places for second-hand shopping and re-selling fashion on the Internet, one of which is the e-commerce website Poshmark.com. By pushing users to engage with Poshmark-content on and off the Poshmark website, the company takes an active part in creating a community and building a cross-website network to boost sales on the site. One way this is done is by advising sellers to publish new additions in their inventory on social media sites like Twitter. We applied text- and network analysis to a set of collected Twitter data, and compiled qualitative observations in order to understand the community structure, communication flow, and identify behavioral patterns in the Poshmark community on Twitter. Our findings imply that the Poshmark community is not an organically grown community, and that the community is used as a strategic marketing tool created by the Poshmark company. Poshmark actively creates and upholds the community by pushing members to share Poshmark content, and encouraging them to be more engaged in the Poshmark community on Twitter. We found problems regarding what could be considered social spam in the content the Poshmark company advises their sellers to share on Twitter, and identified possible concerns regarding the use of Twitter as an external customer service. To improve the user experience on Twitter, we recommend Twitter to be harsher in both what they judge as breaking spam policy and their handling of it. As a solution for unsystematically handled customer service inquiries, we also suggest extending Twitters' features for businesses to better support such a service.

Keywords: Twitter, Social network analysis, Text analysis, Fashion, Community, Poshmark.

INTRODUCTION

Since the online auction site eBay took the yard sale online when it was founded as AuctionWeb in 1995 (Cohen, 2003), several other websites offering similar services have emerged on the Web. Two decades into the 21st century, there is an abundance of places for second-hand shopping and re-selling on the Internet, one of which is the e-commerce website Poshmark.com[1]. The users – called *Poshers* by the company – use the site to make money from selling both used and new items, most of which are clothes, and in doing so are taking part in an online community by coming together in a virtual space to engage in social activities with others (Kraut & Resnick, 2011).

The Poshmark community is as much created by the company behind the website as it is organically formed by the people using the space. Like Boyd (2002) argues that eBay is a community of commerce that was created by simply "rhetorically calling a community into being" (Boyd, 2002), the same can be argued for Poshmark: by placing new user in a pre-created network of Poshers upon first registering to the website, the company ensures that users will be connected – even if the connections are fabricated. According to Boyd (2002), the main function of eBay's rhetorical community building is to make people using eBay feel that it is safe to participate in online auctions by "reinforcing the power of community as an instrument of trust" (Boyd, 2002). Similarly, Poshmark can be argued to use the construction of community as a tool for increasing their commercial success. By pushing users to engage with Poshmark-content on and off the Poshmark website, the company takes an active part in building a cross-website network to boost sales on the site. One way this is done is by advising sellers to publish new additions in their inventory on other social media sites, like Twitter, by linking those profiles to their Poshmark account and then publish the listings with additional hashtags on other sites.

On Twitter, a common hashtag to add to the Poshmark-listings is "fashion", which inserts the Poshmark sellers on Twitter in the larger fashion community on the site. Seen in relation to the broad fashion community on Twitter, users connected to the Poshmark-website can be seen as a sub-community at the same time as it is as a community of its own. In this report, we will look closer at the Poshmark fashion community on Twitter by examining a dataset containing tweets that include the hashtag *fashion* (#fashion) posted between 13th and 25th of September 2021. By looking in-depth at this community, our aim in this report is not only to present an empirical study of the community in question but also to explore how Twitter is used by the company behind the Poshmark website to actively create its own community, and in connection to this highlight problems that arise from using Twitter in this way. To accomplish this, our exploration of the dataset as it pertains to the Poshmark-community will be guided by three main research questions, namely 1) *how are the Twitter users who frequently use the hashtag 'fashion' together with Poshmark-related content connected in terms of directed communication?,* 2) *what topics connect the members of the community?,* and 3) *what is Poshmark's part in the creation of its community?* The first question will be looked at with the help of user network analysis, the second question by text analysis using text mining techniques, and the third question will be discussed by drawing on Boyd's (2002) notion of a rhetorical community and results from a qualitative observation of selected members of the community.

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1 See http://poshmark.com

In the following section, we will give a brief background on the field of social media analysis research in general, as well as some relevant studies regarding Twitter in particular. We will then in the methodology section describe the data collection process, as well as how the data was cleaned before being used for text- and network analysis. Here, we will also discuss the main computational methods we used in our text- and user network analysis. Next, we present our findings from said text- and network analysis, which is then followed by a discussion of our findings. In connection to our findings we will also discuss problems we have noted regarding the Twitter platform and how it is used, as well as suggest solutions and highlight some considerations. Lastly, in the final section, we will sum up and conclude this report.

BACKGROUND

The continuous development of Web 2.0 technology along with the growing popularity of social media platforms have enormously enriched data-based research such as social media analysis (Markscheffel et al., 2012). Social media analysis is based on computational and analytical methods from mathematics, informatics, and sociology (Markscheffel et al., 2012; Chen et al., 2014) and follow two main approaches, a *content-based* and a *structure-based* approach. Studies following the content-based approach use messages, hashtags, URLs, and trending topics on the sites, and are often focused on discovering users' preferences, emotions, interests, and demands through language or text analysis (see for example Aghababaei & Makrehchi, 2017). With the structure-based approach, research focuses on extracting the structural information from social media graphs for understanding social relations, interests, and hobbies (influence analytics). Depending on the research objectives, the focus is either user-centered, like followers and followees (see for example Lee et al., 2010), or focused on action-based activities such as replies and retweets (see for example Guerrero-Solé, 2018, and Housley et al., 2018). Commonly, there are a set of metrics used within network analysis, including modularity, centrality, and degree. These metrics enable statistical identification of the user network shape and communities, nature of interaction flows, and the main influencers in a given network.

In the last decade, Twitter as a social networking platform and the content produced on it have been studied extensively within a range of academic disciplines. Part of the research has focused on the use of Twitter by companies, both from the perspective of the business and the public. Xiong and MacKenzie (2015) studied how Australian companies use Twitter as a communication tool for business purposes, finding that the purpose for using Twitter differed between industries but that the overall most common uses were for promoting the company, publishing news, and addressing customer service-related concerns. Their paper endorses the validity of the use of Twitter for business communication purposes for all types of organizations (Xiong & MacKenzie, 2015). Greene et. al. (2021) studied how companies selling food and beverages "personify" their brands as a way to increase engagement, and with that more effectively market themselves on Twitter, and argued that this new type of advertisement might have consequences for public health. Also exploring the idea of marketing through engagement, Armstrong et. al. (2016) studied the social media marketing strategy on Twitter by the Los Angeles Kings hockey organization, arguing that it illustrates "the potential collaborative efforts of an organization and its consumers" (Armstrong et. al., 2016) which they see as an opportunity to develop a relationship between brand and consumer. This report will situate itself in the same research area by studying the Poshmark community on Twitter from perspectives of company-driven community creation, using Twitter for marketing and business purposes, and the effects of this for both community and company.

METHODOLOGY

Scripting approaches were used to collect and preprocess the main dataset that lays the ground for our analysis in this report. Taking an exploratory approach to assessing the data, we used text and data mining tools, primarily graphical techniques such as wordclouds and network visualizations to discover and investigate the Poshmark-community. By applying principles from exploratory data analysis (EDA), we were able to discover features of interest in the dataset (Wilkinson Saldaña, 2018). These areas of the data later guided us in our closer investigations and subsequent findings.

The text analysis was performed with tools from the web-based toolkit Voyant Tools (Sinclair & Rockwell, 2016), an environment for text reading and analysis, and with the Python libraries Gensim (Řehůřek & Sojka, 2010) and pyLDAvis (translated from Sievert & Shirley, 2014), developed for topic modeling and topic visualization, respectively. Topic modeling and our use of latent Dirichlet allocation (LDA) topic models will be explained further in connection to the results.

We used the open-source software Gephi (Bastian et. al., 2009) for network manipulation, visualization, and exploration in order to perform a user network analysis. Gephi offers a variety of functions for statistical analysis, which we applied to our data (e.g. density, modularity, degree, etc.). Simultaneously, we incorporated manual-observational approaches via the Twitter feed and the web-based statistical tool Social Bearing[2] to compile qualitative observations of the users' communication based on the Twitter typology of action developed by Housley et. al. (2018). The specifics of these methods will, as with the topic models, be explained in more detail in context of the results.

In the rest of this section, we will now go into some detail about how the data was obtained, and how the data was pre-processed before being used in the text- and network analysis.

Data collection

This report is largely based on a dataset containing close to 147 000 tweets posted on Twitter between 13th and 25th of September 2021. The data was retrieved from Twitter using Tweepy[3], a Python library for accessing the Twitter application programming interface (API). The Twitter API provides functions for collecting raw Twitter data based on your chosen parameters, our being the use of #fashion in the tweet, English language, and the date range. For each tweet collected, we stored additional information such as user name, profile description, and number of followers. The fetched data was stored according to the API response into a stand-out file with the CSV format to be used later for structural- and text analysis.

[2] https://socialbearing.com/
[3] https://www.tweepy.org

The data used for the qualitative analysis were gathered using the free version of the subscription website Social Bearing. We accessed a minimum of 200 tweets per observed profile during the 15th and 16th of October[4], from which we chose posts to observe the engagement with by looking at their replies. The posts had to fulfill two criteria: a) belong to a unique category, and b) have at least 2 replies. Apart from this they were chosen at random. As soon as we sampled these posts, we observed the top shown replies, as displayed on the Twitter feed. This was done individually for each of the sampled posts.

Text analysis

Pre-processing for text analysis

Before being used for text analysis, the corpus was pre-processed to better suit the text mining techniques that we applied. Only the tweets in themselves were used in the analysis, not other fields in the dataset containing text. Standard pre-processing steps were applied to the tweets using the Gensim library (Řehůřek & Sojka, 2010), the Natural Language Toolkit (NLTK) library (Bird et. al., 2009), and WordNet Lemmatizer (Princeton University, 2010). The NLTK list of stopwords for the English language was used to remove overly common words from the corpus.

The corpus was divided and pre-processed three ways: as a whole, and divided into two sub-corpora based on membership in the Poshmark sub-community. Tweets belonging to the Poshmark set were filtered by the mention of "Poshmark" in the tweet's corresponding user description, while non-Poshmark tweets were filtered by not mentioning Poshmark in the tweet. As links can be an informative metric in analyzing communication, URLs were kept in the corpora to start, and taken out when working closer with the text.

Topic modeling

Based on the assumption that we might gain insight into how communication within the Poshmark community functions by understanding what topics are being discussed in the community, we used probabilistic topic modeling on the two sub-corpora. Topic models are a way to organize large, unlabeled corpora into computer-generated categories (Dobson, 2019). As explained by David Blei (2012), topic modeling can help uncover "hidden thematic structure" in a large collection of texts by having an algorithm first identify tightly co-occurring terms in a corpus, and then group them based on the probability of the terms occurring together (Blei, 2012). These groups of terms, which make up the *topics*, can be used to interpret possible themes in the corpus as well as the importance of said themes (Dobson, 2019). One of the most used algorithms for topic modeling is latent Dirichlet allocation, which also is the one we used here. Terms with very low frequency, as well as terms with very high frequency, are assumed to be of less importance when creating topics (Maier et. al., 2018), and as such, we based the models on terms that appear at least 30 times in the respective corpus and not in more than 90% of the documents (tweets) of the corpora. Additionally, topic models — regardless of algorithm — use term frequency-inverse document frequency (TF-IDF) to give weight to words that are assumed to be more important for topics (Dobson, 2019; Manning et. al., 2008).

[4] This meant mismatching dates with the data retrieved earlier, as the free version of the website limits the data-loading to the past 7 days. The reason for choosing this tool despite discrepancies in the data was its functions for filtering and handling data, and performing descriptive- and sentiment analysis.

Network analysis

Pre-processing for network analysis

In order to perform our network analysis through Gephi, we needed to reconstruct the data into edges and nodes. The nodes represent the profiles that had quoted, mentioned, or retweeted other profiles. We identified these profiles in the dataset (nodes), then mapped their type of connection as edges while we mapped both the profile that tweeted as a source and the other profiles as a target, which was done for each connection. In the case none of these was found, the record was dropped/ignored while this data-cleaning was applied for the three mentioned types of communication.

Methods for network analysis

Modularity classification determines distinct clusters within a network graph according to the relationship strength between the nodes (Cherven, 2015). In order to identify the number of different sub-groups in the Poshmark network, we ran the modularity test developed by Blondel et. al. (2008).

Centrality is a set of metrics within network analysis that determines "the role of an individual within a society [...] its influence or the flows of information on which he can intervene" (Rochat, 2009, p.1). Betweenness Centrality Ranking (BCR) refers to the algorithm that defines the robustness of information flow by locating the shortest path to and from a particular node (Cherven, 2015, p.200).

The weighted degree of a certain node equals the number of nodes connected with it (Wasserman & Faust, 1994). A weighted In-degree means the number of times a user was retweeted or mentioned, oppositely, the Out-degree represents the number of times a user retweets or mentions other users (Hanneman & Riddle, 2005).

Limitations

When we first fetched the data, we did not include the retweets in the API query request, which consumed time to identify the IDs of the tweets then fetch the required data again to be able to pursue the network analysis. Another limitation due to the time constraints of this study, is the incompleteness of the dataset for an in depth analysis of the Poshmark community on Twitter. As we collected tweets containing *#fashion*, tweets from the Poshmark community not containing this hashtag could not be part of our computational analysis. Despite this limitation, however, we believe that our analysis of the community holds value.

RESULTS

Text analysis

Text exploration with Voyant Tools

To get an initial understanding of the corpus, we used Voyant Tools (Sinclair & Rockwell, 2016) to create an interactive wordcloud of the tweets with the *Cirrus* function, choosing to look at the 200 most frequent terms across the corpus (see appendix A). The wordcloud makes it apparent that a significant part of the Twitter fashion community is members of the aforementioned e-commerce website Poshmark. The practice of linking to other web pages is also something that stands out. As previously explained, URLs were intentionally kept in the pre-processing of the corpus, as the frequency of links in the corpus can be an interesting aspect to consider when looking at how the community communicates. The link indicator “https” appears a total of 258 321 times[5] in the corpus made up of 146 844 tweets, making the use of links something that should be considered in an analysis of the community and how it communicates.

When applying the *Contexts* function in Voyant to look at tweets by selecting specific terms in the wordcloud, it is clear that the big terms in the wordcloud, for the most part, belong to tweets published by Poshmark sellers. The Poshmark-tweets are formulaic to a high degree: most of them consist of the phrase “So good I had to share! Check out all the items I'm loving on @Poshmarkapp”, followed by hashtags and a link to what we discovered are the user’s Poshmark profile. Additional wordclouds were created to show the terms specific to the sub-community made up of Poshmark users and, as a point of comparison, how the corpus looks with the tweets posted by Poshmark users removed.

Figure 1. *Cirrus (Voyant Tools) of the Poshmark sub-corpus. (Left.)*
Figure 2. *Cirrus (Voyant Tools) of the non-Poshmark sub-corpus. (Right.)*

The two wordclouds (figure 1, figure 2) display a stark difference in how the topic of fashion is engaged with through Twitter by the Poshmark-community vis-a-vis the non-Poshmark users. Apart from the pre-written phrase, the most frequent terms in tweets posted by Poshmark-members are almost exclusively names of brands, presumably written in the context of what kind of clothes a tweet is advertising. In contrast, it appears that the tweets not connected to Poshmark are more descriptive in their message, while at the same time they too are focused on either buying or selling to some extent (“ebay”, “buy”, “shop”, “sale”, “smallbusiness”, etc.).

Topic modeling with latent Dirichlet allocation

Using Gensim (Řehůřek & Sojka, 2010), we modeled 10 topics each for the Poshmark corpus and the non-Poshmark corpus. The topics reinforced our interpretation of the wordclouds. With the highly frequent terms filtered out, the Poshmark topics are essentially collections of brand names without much internal coherence, while the topics from the non-Poshmark corpus point

[5] From the pattern “http*”

toward certain themes (see figure 3). By visualizing the topic distribution with an intertopic distance map generated with pyLDAvis (Sievert & Shirley, 2014), we could see how similar the topics are to each other. As topics that are closer together have more terms in common, the visualizations of the models strengthened our interpretation of the communication in tweets in the Poshmark community as being highly repetitive and almost exclusively focused on advertising, while the non-Poshmark community is more diverse in their communication (see figure 4).

Topic 1	Topic 2	Topic 3	Topic 1	Topic 6	Topic 8
freepeople	vintage	levis	photography	jewelry	baby
michaelkors	oldnavy	katespade	love	necklace	vintage
zara	victoriassecret	adidas	instagood	earrings	etsy
disney	lanebryant	luckybrand	like	silver	amp
forever	underarmour	gap	model	gold	kid
chicos	unbranded	raedunn	beautiful	ring	watch
betseyjohnson	newyorkcompany	urbanoutfitters	style	ebay	girls
worthington	eileenfisher	anntaylor	photooftheday	jewellery	cute
timberland	maurices	columbia	follow	womenswear	kidsfashion
umgee	aeropostale	charlotterusse	beauty	womensfashion	children

Figure 3. *LDA topics created with Gensim. To the left, the 10 most probable words for the first three topics from the Poshmark corpus; to the right, the 10 most probable words for three of the most legible topics from the non-Poshmark corpus.*

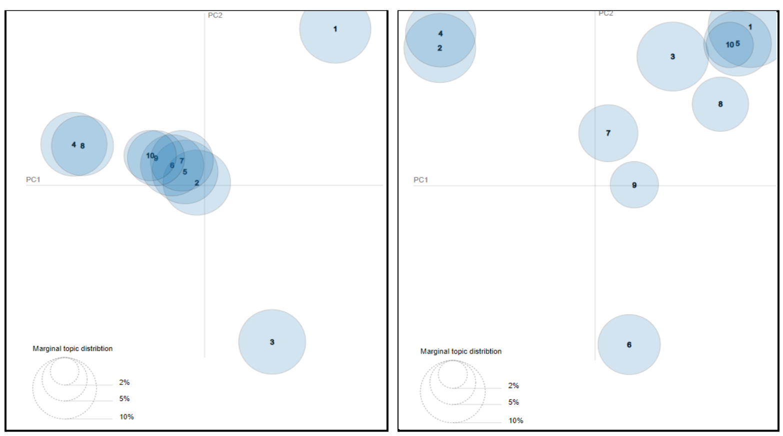


Figure 4. *Intertopic distance maps generated with pyLDAvis. Poshmark to the left, non-Poshmark to the right.*

User Network Analysis

Community structure and shape

After preprocessing the gathered data we used Gephi (Bastian et. al., 2009) to plot the shape of the community structure. The resulting visualization of the user network shows that it consists of 695 nodes, representing different Twitter user profiles (including individuals, organizations, and companies), which are connected by 811 edges that represent the interactions between these users (figure 6). Figure 6 shows the types of interactions, being 88% Mentions (colored in purple), 11% Retweets (colored in green), and 01% Quotes (colored in blue). To view the predominant direction of connections that determines the interaction flows in Appendix B.

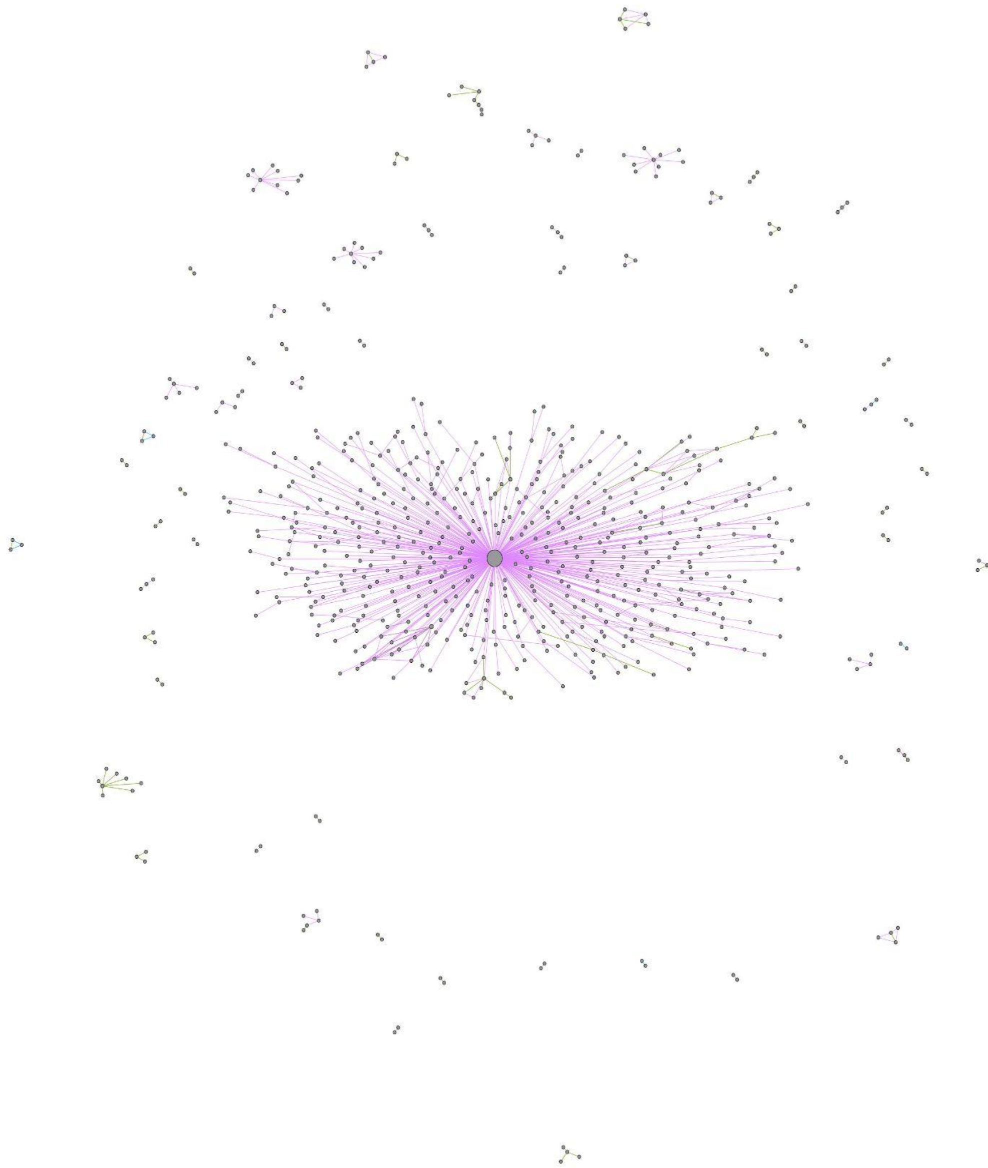


Figure 6. *Innermost part of User Network showing the type of connections.*

Modularity

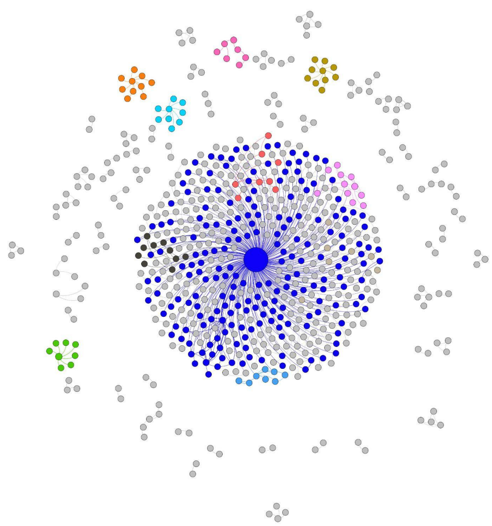
The modularity test resulted in a total of 178 different sub-groups for the whole #fashion community. We decided to only colorize the largest 11 sub-groups (with modularity ≥ 1.01%), which have the most interconnections in comparison with the rest of the network (figure 7 or Appendix B). By looking at the users' profiles that exist in the clusters, we found that they were photographers, designers, or studio workers/owners while they were constantly mentioning and promoting each other; therefore, we interpret the connections to be based on similar interests, relations in the real world, or having mutual followers/friends. The figure also indicates that the node @Poshmarkapp has different sub-groups although it connects all the nodes (users), meaning there are several distinct smaller conversations held between different users who follow @Poshmarkapp.

Centrality

Running the centrality analysis on the Poshmark community showed that the highest centrality measure (BCR = 64) was scored by the username @pat940atwatsons within the blue sub-group, a lower centrality measure (BCR = 6) for @susieqs2 who connects to the dark grey sub-group, followed by @jenniegirlsclos in the light pink sub-group (BCR = 3). These profiles were later further investigated qualitatively to understand why they appear to be mentioning or retweeting other Twitter accounts/users the most in comparison to other users.

Degree

Considering the time limitations of this project, we focused on identifying the main degree measures based on the centrality results and only considered the nodes connected to @Poshmarkapp or designated from its sub-groups, resulting in Table A that is sorted based on the degree.



Username	Degree	In-degree	Out-degree
@poshmarkapp	356	356	0
@pat940atwatsons	39	8	31
@flai1234	15	0	15
@giftcod	13	0	13
@emilyamazon	9	0	9
@jenniegirlsclos	8	4	8
@susieqs2	5	2	3

***Figure** 7. User Network showing the inner communities. (Left.)*
***Table A**. The main Degree, In-degree, and Out-degree measures. (Right.)*

Qualitative observations

Our qualitative analysis of the Poshmark community had two foci: observing and analyzing tweets and retweets by @poshmark, as well as replies to them, and observing and analyzing the Twitter feeds of the 7 profiles shown in table A. By using the Twitter typology of actions developed by Housley et. al. (2018), we labeled the observed tweets and replies as belonging to at least one category. The categories from the original typology that we used were *agreement*, *disagreement*, *criticism*, *requests*, *praise,* and *informational*, to which we added our own categories *rewards*, *encouragement*, *encouraging contribution*, and *promotions* for the tweets. For the replies, we added the categories *questioning the actions taken for inappropriate* *behaviour* and *advice*. The second layer of Housley et. al. 's (2018) typology divides the actions based on their engagement or un-engagement (praise, criticism, request) and explicit or implicit sentiment (agreement, disagreement) with the topic of the posted tweet, which we also took into consideration in our analysis. The added categories were divided based on engagement or un-engagement.

The observation of @poshmarkapp's tweets (27.5% from a total of 200 tweets) showed that the majority of the tweets belong to the *encouraging engagement* and *encouragement* categories (see appendix C). The engagement tweets were phrased as short, casual questions which asked for sellers' contributions in an indirect manner, while the encouragement appeared in two forms: tweets that consisted of verbal encouragement (pep-talk, inspirational quotes) and in the form of rewards that encouraged sellers to engage with the community and other members. *Advice*, *promotions*, and *rewards* were other prominent categories. In some tweets, @poshmarkapp was advising their sellers regarding different topics, while other tweets were found to promote specific sellers or to promote competitions with prizes.

Observing @poshmarkapp's replies showed that they are mainly responses to individuals contacting @poshmarkapp, and the majority of the individuals' concerns were either forwarded to be handled by the platform moderators or handled as direct messages (DMs). These cases caused a deviation of the conversations from the main posted topics into private and sub-conversations.

From the side of sellers replying to the tweets posted by @poshmarkapp, we identified that only a few sellers' replies included an explicit agreement with the topics in question and that most of the other sellers' replies did not engage directly with the topics. Such unengaged replies were requesting help with profile issues (e.g. "I need help I haven't received my payment for the items I've sold"), questioning the actions taken for inappropriate behaviors/post listings, criticizing the inappropriate posts/profiles on the original Poshmark platform, or advising the handling of inappropriate posts/profiles (see appendix D).

The qualitative observations of the seven profiles selected based on the results from the centrality and degree analysis of the user network showed that all observed members of the Poshmark community frequently used templates to tweet links to both Poshmark and other e-commerce sites. In the case of the Poshmark advertisement, the tweets were both self-promoting and promoting other sellers' listings, either in the form of retweets of other sellers' listings, or tweets linking either own listings or listings from other sellers. Apart from @poshmarkapp, the profiles with the highest degree measures (@pat940atwatsons, @flai1234, @giftcod) all showed a similar promotional behavior pattern of frequently retweeting other sellers' listings, explaining their high out-degree measure.

DISCUSSION

The Poshmark community is interesting in that it is not an organic community, grown through some shared set of interests: although it is centered around buying and selling fashion, and the community members certainly do share this interest, the creation of the community can be viewed as a strategic marketing tool created by the company rather than formed by the users the website connects. In this view, the Poshmark community on Twitter that we have observed can be argued to be an example of a new type of community – or perhaps more aptly, a fabricated community – that is created by a company, mainly for that company's benefit. Like Boyd (2002) argues that eBay is a community of commerce that was rhetorically called into being by simply being titled as such, the Poshmark community – and more narrow the Poshmark community on Twitter – can be argued to have a similar origin.

To be a community, however, the members need to participate in it. Here too Poshmark takes an active part in creating and upholding the community by both pushing members to share Poshmark content, and trying to get users to more actively engage in the Poshmark community on Twitter by for example posting tweets with questions for the community to answer. While the encouragement for members to contribute to the community by engaging with the tweets from the official Poshmark profile on Twitter is benign as a business marketing strategy, a more questionable strategy for pushing community engagement is the way the company advises Poshmark sellers to advertise items they are selling on Twitter.

When the character limit of tweets was increased from 140 to 280 in 2017, the change had little impact on the length of the average tweet (Rosen, 2017). The possibility of including more information has however made it possible to use Twitter in novel ways. In the tweets from the dataset this report is based on, 93 percent were over 140 characters in length, indicating that people who tweet about topics adjacent to fashion do make use of the increased character limit. This is however not due to added content, but the frequent use of links in the tweets – in our dataset consisting of close to 147 000 tweets, there were over 258 000 links. In the case of the Poshmark community, the links are part of the sellers' advertising of, usually their own, Poshmark profiles. This type of advertising on websites outside of Poshmark.com is something the Poshmark website encourages their sellers to do, and they provide a pre-written template for doing it, making these tweets extremely similar.

While Internet spam – unsolicited messages sent in bulk – on online social networking sites usually are described as "undesirable, malevolent, unsolicited content or behavior" (Rao et. al., 2021), there is ground to consider the formulaic tweets Poshmark encourages their sellers to use as a kind of non-malevolent social spam. Although the tweets are not posted in bulk by one or a few people, like more typical social spam (see ibid.), they are posted with high frequency when considered together, making their presence in Twitter feeds have a spam-like appearance. The original tweets are accompanied by pictures from the items' listings on Poshmark, which are not included in our dataset, but otherwise, it is hard to separate the tweets from each other: as shown in the topic models of the Poshmark- and non-Poshmark corpora, it is clear that there is a lack of authentic conversations being held in the tweets posted by sellers in the Poshmark community on Twitter.

The tweets advertising Poshmark sellers are posted on the users' own timeline, and as such not directly targeting individuals, but the use of hashtags does mean that the tweets will appear in other users' spheres much like regular social spam. In the spam policy of the Twitter platform, there is a clear statement that it is forbidden to use Twitter in a way that disrupts other users' experience, clarifying that this includes "repeatedly posting identical or nearly identical Tweets" (Twitter, 2020). The formulaic Poshmark tweets seem to fit this description.

In our observation of specific profiles within the Poshmark community, there were indications that some users exclusively post tweets following a set template with links to other sites, such as Poshmark. This behavior also operates on the line of what is acceptable according to the spam policy, which states that it is not allowed to "repeatedly [post] Tweets or sending Direct Messages consisting of links shared without commentary, so that this comprises the bulk of your Tweet/Direct Message activity" (2020). Although these tweets do contain some commentary, it is in a very loose sense. Since Twitter has options to take action against non-malicious spam content on tweet-, direct message-, and account level (Twitter, n.d., *a*), the question here is if Twitter does not regard this behavior as spam, or if it is a lack of resources to deal with spam. Regardless, to improve Twitter as a platform we argue that this kind of non-malicious social spam should be handled harsher by the platform, as it disrupts the user experience — if not for the Poshmark community, then for people outside of it who follow the same hashtags. As these tweets are encouraged by the Poshmark company, it is difficult to judge how their presence is seen from within the Poshmark community. It is possible, perhaps even likely, that they are not considered to be an annoyance. It is important to remember, however, that the Poshmark community does not exist in a closed-off space — with the use of hashtags, different communities will overlap in the Twitter-sphere.

In our qualitative observation of the community on Twitter, we also noticed that much of the conversations observed focused on criticizing the company for not properly handling users selling counterfeit items. Several of the replies to tweets posted by the official Poshmark profile expressed disappointment regarding the situation, and anger toward the company for not taking enough action against people not following the community guidelines, or right out scamming other members by selling non-existing or counterfeit items. Poshmark appears to reply to most of these concerns as well as forward it to the platform moderators, indicating that Twitter is being used as an additional customer service page. This type of consumer-company interaction has become a common use of Twitter as a platform by different types of businesses, and is something that Twitter explicitly suggests companies do to "Provide timely customer-service" (Twitter, n.d., *b*).

That Twitter is being used as an extension of traditional customer service was apparent in our observation of the community. With a significant amount of concerns directed at the company by the Poshmark community now being posted as replies to unrelated tweets (critical un-engagement), however, the system is unstructured, and risks messages getting lost in the threads. Having a declared space for questions and concerns could make the interaction easier and improve the user experience. For these reasons, we believe the development of an extended feature for Twitter to allow businesses to be more systematic in their consumer service communication could prove beneficial for both companies and consumers. At the same time, however, there is a concern that such a solution would not necessarily serve the Poshmark community. Depending on if a dedicated place for customer service would lead to more effort being put into resolving the problems the community is experiencing, or if it would simply mean that critical opinions were moved but not resolved, not redirecting these types of concerns might be better for transparency

Outside of the critical voices, there were signs of users being happy with the community despite its problems. In replies that did not fall under the criticism category, community members showed appreciation of the website – and with that the community – by engaging with tweets in a positive manner. That the company manages to get parts of the community to actively participate in an engaged way — despite being what could be described as a fabricated community, created by the Poshmark company rather than the members, and despite frequent criticism regarding enforcement of rules — shows evidence that the Poshmark platform has a reasonably good model for managing the community and using its existence as a way to further their business. To improve overall community morale, however, the critical voices should be listened to more closely. Part of the problem seems to be, from what we have observed, that their concerns are not heard. According to the messages in our qualitative observation, they experience that their questions and criticism are not being answered by the company, furthering their disappointment with the community. As many Poshmark sellers seem to take their grievances to Twitter, as opposed to the (nowadays) more common form of customer service through e-mail, having a dedicated place for raising these concerns on the Twitter platform, as proposed above, might be a way to improve communication with the company, and with that improve the community's overall satisfaction.

CONCLUSION

In this report, we have looked at how the community around the e-commerce website Poshmark.com uses Twitter, as well as how the Poshmark company uses Twitter as a community-building marketing tool. By applying text- and network analysis methods to a set of collected Twitter data in connection to qualitative observations of parts of the community, we have attempted to understand the community structure, communication flow, and identify behavioral patterns of community members. Our findings imply that the Poshmark community is more a creation of the company than created by the community members, and that the community is used as a strategic marketing tool by the Poshmark company. Poshmark actively creates and upholds the community by pushing its members to share Poshmark content, and encouraging them to be more engaged in the Poshmark community on Twitter. We found problems regarding what we consider to be spam content, which incidentally is content the Poshmark company advises community members to share. An additional problem found is how Twitter appears to be used as an external, unstructured customer service resource, possibly leading to raised concerns from the community being lost in the replies. As a solution to this problem, we suggest extending Twitter's features for businesses to include opportunities for more structured customer service.

REFERENCES

Aghababaei, S., & Makrehchi, M. (2017). Activity-based Twitter sampling for content-based and user-centric prediction models. *Human-centric Computing and Information Sciences,* 7(1), 3. doi:10.1186/s13673-016-0084-z

Bastian M., Heymann, S., & Jacomy, M. (2009). *Gephi: an open source software for exploring and manipulating networks.* [Conference paper]. International AAAI Conference on Weblogs and Social Media, San Jose, USA. Retrieved from https://gephi.org/publications/gephi-bastian-feb09.pdf.

Bird, S., Klein, E., and Loper, E. (2009). *Natural Language Processing with Python.* O'Reilly Media Inc. http://nltk.org/book

Blei, D. M. (2012). Topic modeling and digital humanities, Journal of Digital Humanities, 2(1). Retrieved from http://journalofdigitalhumanities.org/2-1/topic-modeling

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment*, 2008(10), P10008. Retrieved from https://arxiv.org

Boyd, J. (2002). In community we trust: Online security communication at eBay. *Journal of Computer-mediated Communication*, 7(3). doi:10.1111/j.1083-6101.2002.tb00147.x

Cherven, K. (2015). *Mastering Gephi Network Visualization.* Birmingham, UK: Packt Publishing Ltd. Search in Google Scholar

Cohen, S. A. (2003). *The perfect store: Inside eBay*. Retrieved from https://archive.org

Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile networks and applications,* 19(2), 171-209. doi:10.1007/s11036-013-0489-0

Dobson, J. E. (2019). *Critical digital humanities: The search for a methodology.* Urbana, Illinois: University of Illinois Press.

Greene, T., Seet, C., Rodríguez Barrio, A., McIntyre, D., Kelly, B., & Bragg, M. (2021). Brands with personalities – good for businesses, but bad for public health? A content analysis of how food and beverage brands personify themselves on Twitter. *Public Health Nutrition,* 1-10. doi:10.1017/S1368980021001439

Guerrero-Solé, F. (2018). Interactive Behavior in Political Discussions on Twitter: Politicians, Media, and Citizens' Patterns of Interaction in the 2015 and 2016 Electoral Campaigns in Spain. *Social Media + Society*. 4(4). doi:10.1177/2056305118808776

Hanneman, R.A. & Riddle, M. (2005). *Introduction to social network methods.* Riverside, CA: University of California, Riverside. http://faculty.ucr.edu/~hanneman/

Housley, W., Webb, H., Williams, M., Procter, R., Edwards, A., Jirotka, M., Burnap, P., Stahl, B. C., Rana, O., & Williams, M. (2018). Interaction and Transformation on Social Media: The Case of Twitter Campaigns. *Social Media + Society.* doi:10.1177/2056305117750721

Kraut, R. E. and Resnick, P. (2011). *Building successful online communities: Evidence-based social design.* Cambridge, Mass: MIT Press. Search in Google Books

Lee, C., Kwak, H., Park, H., & Moon, S. (2010). Finding influentials based on the temporal order of information adoption in twitter. *Proceedings of the 19th international conference on World wide web* (pp. 1137-1138). doi:10.1145/1772690.1772842

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., . . . Adam, S. (2018). Applying LDA Topic Modeling in Communication Research: Toward a Valid and Reliable Methodology. Communication Methods and Measures, 12(2-3), 93-118. doi:10.1080/19312458.2018.1430754

Manning, C. D., Raghavan, P, and Schütze, H. (2008). *Introduction to information retrieval.* Retrieved from http://informationretrieval.org/

Markscheffel, B., Eine, B. & Broszinski, L. (2012). *The Twitter Ecosystem and its Implications for Informetrics Research.* [Conference paper]. 8th International Conference on Webometrics, Informetrics and Scientometrics & 13th Collnet Meeting, Seoul, Korea. Search in Google Scholar

Princeton University. (2010). About WordNet. *WordNet*. https://wordnet.princeton.edu

Rao, S., Verma, A., & Bhatia, T. (2021). A review on social spam detection: Challenges, open issues, and future directions. *Expert Systems with Applications*, 186. Retrieved from doi:10.1016/j.eswa.2021.115742

Řehůřek, R., and Sojka, P. (2010). Software Framework for Topic Modelling with Large Corpora. *Proceedings of LREC 2010 workshop New Challenges for NLP Frameworks*. Valletta, Malta: University of Malta, 2010. p. 46-50. Retrieved from http://www.lrec-conf.org/proceedings/lrec2010/workshops/W10.pdf

Rochat, Y. (2009). Closeness Centrality Extended to Unconnected Graphs: The Harmonic Centrality Index. [Conference paper]. ASNA, Zurich, Switzerland. Search in Google Scholar

Rosen, A. (2017). Tweeting made easier. *Twitter blog.* Retrieved from https://blog.twitter.com/official/en_us/topics/product/2017/tweetingmadeeasier.html

Sievert, C., and Shirley, K.E. (2014). LDAvis: A method for visualizing and interpreting topics. (Workshop paper]. Workshop on interactive language learning, visualization, and interfaces. Baltimore, June 27, 2014. Retrieved from https://nlp.stanford.edu/events/illvi2014/papers/sievert-illvi2014.pdf

Sinclair, S. & Rockwell, G. (2016). *Voyant Tools*. Web. http://voyant-tools.org/.

Twitter. (2020). Platform manipulation and spam policy. *Twitter.* Retrieved from https://help.twitter.com/en/rules-and-policies/platform-manipulation

Twitter. (n.d., *a*). Why use Twitter for business? An introduction to Twitter for business. *Twitter.* Retrieved from https://business.twitter.com/en/basics/intro-twitter-for-business.html

Twitter. (n.d., *b*) Our range of enforcement options. *Twitter.* Retrieved from https://help.twitter.com/en/rules-and-policies/enforcement-options

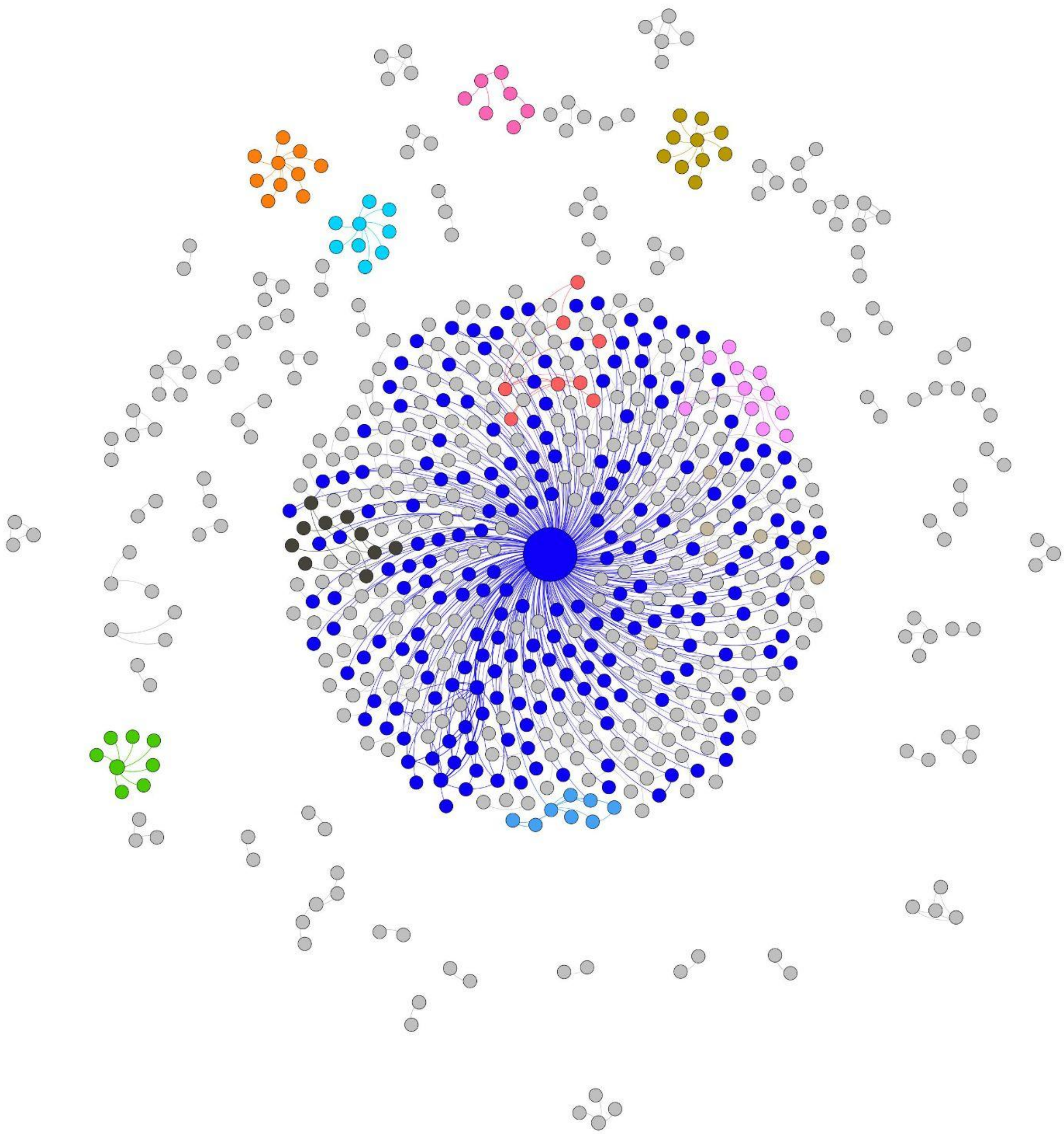
Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications (Structural Analysis in the Social Sciences)*. Cambridge: Cambridge University Press. doi:10.1017/CBO9780511815478

Xiong, F., and MacKenzie, K. (2015). The business use of Twitter by Australian listed companies. *The Journal of Developing Areas*, 49(6), 421-428. doi:10.1353/jda.2015.010

Appendices

Appendix A: Cirrus (Voyant Tools) of the corpus, and cropped close-up.

Appendix B: predominant direction (clockwise) of connection for the user network.



Appendix C: Examples of the coding and categorizing done for the detailed analysis

ID	Plain tweets	Category	Engagement level
#1	"Today, at #PoshFest2021, we shared our exciting vision for becoming the #1 one	Informative	Retweet:15

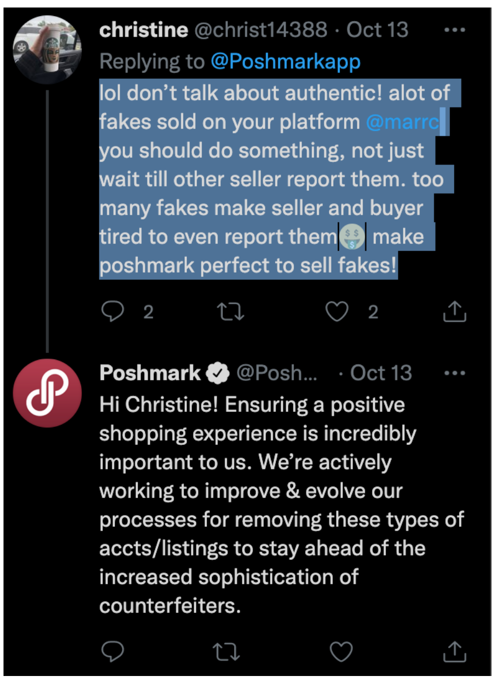
	destination for sellers around the world. How? Read @wwd's @adra_la's interview with our co-founder and newly appointed SVP of Seller Experience,@Tracy_Sun, for the full scoop: bit.ly/2YwjvrU”	(news about the company, launched tools)	Favorite: 1
#2	“The #PoshFest2021 Hackathon Reveal is HERE! 🚨 Today, we announced new seller tools coming to the platform, giving you even more resources to grow your business. 😲 pic.twitter.com/0nEPuitxIy”		Retweet:23 Favorite: 4
#3	“Exciting news! 🙌 Poshmark has acquired Suede One, a platform that combines machine learning, computer vision and expert human review to virtually authenticate sneakers. Learn more about how this deal reflects our focus on strategic investments: bit.ly/PoshNewsroom pic.twitter.com/tJfseIj7v4”	Advice	Retweet: 25 Favorite: 43
#4	Need some Wednesday afternoon fuel? @CNBCMakeIt's @mariamabdallah got the scoop on how Kaitlin Kao turned her reselling hobby into a thriving business on Poshmark — and we couldn't be more proud! twitter.com/CNBCMakeIt/sta…		Retweet: 9 Favorite: 21
#5	“You can't pour from an empty cup. Take care of yourself first.”	Encouragement	Retweet: 96 Favorite: 324
#6	“Stop being afraid of what can go wrong and start believing in what can go right.”		Retweet:63 Favorite:174
#7	“Confidence has no competition.”		Retweet:112 Favorite: 30
#8	“Brands to shop on Poshmark according to @People? From Lululemon to Telfar—check out @alexwarner8's read for more amazing finds: bit.ly/3o38Fo7”	Promotions	Retweet:3 Favorite:4
#9	“Roll call! What's your closet name and how long have you been Poshing?”	Encouraging engagement	Retweet:19 Favorite:119
#10	“Did you drink enough water today?”		Retweet:16 Favorite:75
#11	“What is everyone listening to?”		Retweet:7 Favorite:37
#12	“Instagram is down—if you ran the Poshmark Twitter account, what would you tweet? Best answer wins $100 in Posh Credit. #InstagramDown”	Rewards	Favorite: 128 Retweete:16
#13	“⭐POSHFEST TICKET GIVEAWAY⭐ We are giving away 15 Virtual Tickets with Swag Boxes to this year's PoshFest! It's all happening over on our Poshmark Instagram. Click here to enter for a chance to win: bit.ly/3AwUmLM pic.twitter.com/mDAiNMVOIx”		Favorite: 21 Retweet:5
#14	“University of Toronto student and Poshmark Seller, Kanah (km.customs), shares how you can follow back-to-school fashion trends while being sustainable!	Informative & Promotions	Favorite: 2 Retweet:12

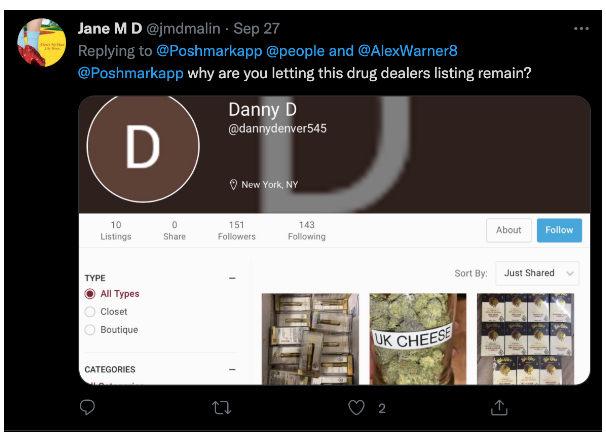
	Watch for more: bit.ly/3lcq7mW”		

Appendix D: A random sample of the replies to such tweets.

<table>
<tr><th>Tweet ID</th><th>Reply</th><th>Category</th><th>Type</th></tr>
<tr><td rowspan="5">#3</td><td>But still no action on all the COUNTERFEIT @vancleefarpels on #PoshMark ?

All sellers that just joined in Oct 21 with a single listing. If I can figure it out, I know you can (IF u wanted to). You’d lose all the commission on them - but isn’t this illegal???

@Counterfeit_Rpt</td><td>Criticism, questioning the actions taken for inappropriate behavior</td><td>Engaged</td></tr>
<tr><td>
</td><td>Criticism, advice for handling inappropriate behavior</td><td>Engaged</td></tr>
<tr><td>Welcome Suede One!</td><td>Agreement</td><td>Explicit</td></tr>
<tr><td>If only you really took the sale of counterfeit items on your platform seriously. You don't even follow your own published counterfeit items policy. My recent experience with Poshmark was eye-opening.</td><td>Criticism</td><td>Engaged</td></tr>
<tr><td>Congrats!!!! We @ownkicks are working on a similar project where our users do not need to upload pictures.</td><td>Agreement</td><td>Implicit</td></tr>
<tr><td>#2</td><td>Except sellers are using the platform for scams! I’ve done my due diligence and reached out to Poshmark support for nearly a week without resolution to an issue with a seller who is clearly scamming poshers. Poshmark has yet to issue my refund despite not receiving the item.</td><td>Criticism</td><td>Un-engaged</td></tr>
</table>

	It’s unbelievable how they allow all these scammers to open accounts daily! I’ve reported them hundreds of times with no results! Scamark!		
	Will Poshmark start penalizing sellers who don’t ship items out? My 400.00 has been taken but the seller still hasn’t shipped. I’ve missed out on several other deals. What will PM being doing about this?	Questioning the actions taken for inappropriate behaviour	Un-engaged
#7	“Also a great platform to be confident on since you can harass and far shame without consequence. You won’t take down harassment posts and comments but you’ll take down authentic listings. Cool system, losers.”	Criticism	Un-engaged
	“I got scammed by someone creating multiple accounts and stealing pictures off of Mercari listings. I emailed support twice for a refund, the first time a couple days ago and still have not received a reply”		
	No, it doesn’t because if your confident in what you do, there is no worry about other’s & what they do. Your positivity & energy radiate in everything you do. Which, comes across in what you do & how you do it…we all have much to learn from you & we love u:):):)	Agreement	Engaged
#8	Please help! My account has been deactivated due to an item that I had shipped but the buyer canceled. I livs in NJ and have been flooded twice this month. Please help!	Request	Un-engaged
		Questioning the actions taken for inappropriate behaviour	
	i need help i haven’t received my payment for the items i’ve sold	Request	
	More of this plz	Agreement	Engaged
#12	Poshmark understood the assignment today	Praise	Engaged
	Poshmark is the main character today. #instagramdown		
	@Poshmarkapp I would tweet that we are no longer going to allow scammers and stop all these people from stealing other Posher’s photos and fake sending these “items” that they don’t even really have.	Criticism	
#13	YOU BANNED MY ACCOUNT FOR CALLING OUT PEOPLE SELLING FAKE BAGS!! I’m a trusted seller with almost 13k followers, 4.8 star average	Criticism	Un-engaged

	and in the top 10%!!! I want my account back! You should be focused on all the fakes on ur platform not the sellers defending you		