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The emergence of core (hash)tags and its effects on performance

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A R T I C L E I N F O

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A B S T R A C T

The informational and social impacts of tags on forming networked publics have drawn extensive scholarly attention. However, existing literature lacks systematic and longitudinal accounts of how trending tags garner community interest and facilitate the promotion of user-generated content. This study addresses this issue by explicating the structures and functions of social tagging, showing how users employed certain tags to improve performance. To provide empirical evidence, we tracked and analyzed social tagging activities in an online community from its early stage for seven years. Over this time frame, very few tags emerged as core tags–the consensus choices that both occurred and co-occurred frequently. Furthermore, the application of core tags, which can represent the tacit rules and platform vernaculars co-defined by the community members, improved performance noticeably more than using peripheral tags. Interestingly, among the core tags, those that possessed linguistic idiosyncrasies particularly contributed to high performance. The findings highlight the complex contingencies of social tagging structures and functions and provide practical implications for users and platforms to strategically manage tag-based networked publics.

1. Introduction

Social tagging (also known as collaborative tagging, collective tagging, folksonomy, social bookmarking, or simply, tagging) allows users to apply terms and phrases to categorize and characterize online content. Recent years have witnessed a burgeoning interest in how tags engage and facilitate the formation of networked publics around specific topics, events, and groups in online communities (Bruns et al., 2016). Networked publics exist when users or subsets of users are bonded by "a common understanding of the world, a shared identity, a claim to inclusiveness, a consensus regarding the collective interest" (Livingstone, 2005, p. 9). Yet, the collective interest can be multifaceted, as has occurred in the COVID-19 pandemic, in which politically opposing tags such as #stayhome (see Petersen & Gerken, 2021) and #filmyourhospital (see Gruzd & Mai, 2020) have emerged and revealed the ideological clash between the subsets of the public. Hence, although selecting a few tags seems to be a simple task, in order to successfully form and maintain publics, tag choices must be consistent with the tacit rules and platform vernaculars emerging from the often-implicit form of collaboration in tagging activities (Bruns & Burgess, 2015; Gibbs et al., 2015). Together, the interdependent users, the tags they use,

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and the content to which tags are attached influence and shape one another in practice, interweaving an intricate network that restricts and regulates tagging syntax and behavior (Halpin et al., 2007; Oh & Monge, 2013; Shepitsen et al., 2008).

Research has suggested that the processes of tagging are further complicated by the performance metrics (e.g., numbers of views, retweets, likes, product sales) associated with different tag choices (Andalibi et al., 2017; Baker & Walsh, 2018; Bruns et al., 2016; Bruns & Stieglitz, 2013). A fundamental question in this research literature is how users leverage tags to reach practical goals, such as facilitating information diffusion (Romero et al., 2011), enhancing user visibility (Blaszka et al., 2012), optimizing search engine results (Geho & Dangelo, 2012), and increasing product sales. Hence, tags are an implicit revelation of the complex dynamics of collective action and human interaction, reflecting community structures from which certain tags arise while conveying rich meanings beyond the words per se (Cattuto et al., 2007; Halpin et al., 2007). Through widespread community use and adaptation, tags help users construct and maintain imaginary shared spaces consisting of interconnected users, content, and tags (Bruns et al., 2016; Gibbs et al., 2015).

Despite the abundance of recent studies on different tags and tagging behavior, scholars have noted the need for more systematic and longitudinal accounts of (1) how consensus tags emerge over time, and (2) the tangible influence tags exert on users' performance (e.g., Rossi & Giglietto, 2016; Wang et al., 2016). To advance this emergent research agenda, the current study focuses on the interplay between the structures and functions of tagging by tracking and analyzing tagging activities in an online community over a 7-year period. For structures, the study addresses how a core-periphery tagging network emerged over time, favoring certain consensus (or "core") tags. For functions, we theorize that sensing core tags is a form of expertise, and that such expertise is diachronically, socially, and dynamically constructed and acquired in large social units through practice and communication (Fulk, 2016). The article concludes with theoretical considerations as well as practical implications for users and platforms that seek to strategically manage tag-based networked publics.

2. Theoretical positioning

Tag vocabularies can include labels that are suggested or mandated by the host platform and/or free form tags that are created or customized by users. This built-in flexibility is intended to make tags efficient, informative, and rich in meaning (Golder & Huberman, 2006; Halpin et al., 2007). In addition to the informational value of individual tags, they may function as normative indicators within a community, which provide tacit guidelines for users on how to both adjust to and influence platform implicit norms that help define the community (Gibbs et al., 2015). Tags often serve to present a collaborative argument on the confluence of shared themes, agenda, and expectations (Baker & Walsh, 2018; Bruns et al., 2016; Enli & Simonsen, 2018; Papacharissi, 2015; Papacharissi and de Fatima Oliveira, 2012). The normative aspect of tagging is especially salient in contemporary social movements and online activist campaigns, where a variety of user-generated tags have become pivotal symbols to connect like-minded individuals and succinct ways of expressing identities and opinions (Papacharissi, 2015).

A distinct feature of tagging activities is that users are exposed to and influenced by each other's tag choices (Cattuto et al., 2007). Meanwhile, users must also have a good sense of what tags would be useful to inform searchers to boost the effectiveness of tagging (Halpin et al., 2007). However, as variants of tags could be applied to a multitude of contents by different individuals (e.g., #stayhome, #stayathome, #stayhomesavelives, #stayhomestaysafe were all used in COVID-19 related content), the lack of predetermined standards also makes the tagging system full of uncertainty. This uncertainty may drive users to rely on others' tagging choices as a reference to calibrate tagging behavior (Gibbs et al., 2015). Through long-term observations, adaptations, and imitations, the seemingly disorganized tagging system is rearranged with certain consensus choices, coupled with other less popular options (Golder & Huberman, 2006; Oh & Monge, 2013). These bottom-up efforts of coordinating consensus tag choices may help cultivate "platform vernaculars" (Gibbs et al., 2015), distinguishing online communities from each other in genres, logics, and styles.

2.1. Structures of tagging: Core, periphery, and hierarchies

Like many other technological artifacts, tags do not act as atoms outside a social realm but are embedded in a concrete and dynamic system, where the contextualization of tags takes place through their connections with users and media content. In the tagging system, users, content, and tags form a three-level structure, a tripartite network in which these three kinds of nodes co-exist, co-function, and co-evolve (Halpin et al., 2007; Oh & Monge, 2013). This structure is of vital importance for understanding the formation and growth mechanisms of the tagging network, because it shows how the seemingly freely-nominated tags are constrained by other types of nodes at play. From a network embeddedness perspective (e.g., Bessi & Ferrara, 2016; Granovetter, 1985), the ongoing construction of relationships between humans and artifacts configures local and global network structures that regulate tagging activities in an implicit manner.

The interdependencies among tags, users, and content also impose constraints on the introduction of new tags to the tagging network. For example, Oh and Monge (2013) found that only a small number of tags that have already been used frequently will be repeatedly used, whereas most of the tags will be used rarely. The intuition is that this "rich get richer" phenomenon may follow the pattern of preferential attachment, whereby new nodes are likely to connect to other nodes that are already well-connected (Barabási & Albert, 1999). Preferential attachment may increase the tendency toward the formation of a core-periphery network structure (Borgatti and Everett, 2000; Rombach et al., 2014). In the context of tagging, the tags that are not used extensively can be driven out to the periphery given their relative disconnectedness, while the tags that both occur and co-occur frequently may form a densely connected core in the network.

While not focusing specifically on the core-periphery structure of tagging, recent studies (e.g., Freelon et al., 2018; Bennett, Segerberg, & Yang, 2018) have noted the tendency for a small number of tags to be used disproportionately more often than most tags in social media activist campaigns. For example, following the rapid emergence of #MeToo in the movement of breaking silence regarding sexual harassment and violence, tags such as #BelieveWomen and #TrustWomen were circulated in the local sections of the movement, but none of these tags rivaled #MeToo in terms of visibility and prevalence (Mack & McCann, 2018). Moreover, when #BlackLivesMatter became a trending tag in the social media protests in 2014 and 2015, counter-protest tags appropriating the same syntax (e.g., #AllLivesMatter, #BlueLivesMatter, #PoliceLivesMatter) were also seen on social media but at a noticeably smaller scale (Gallagher et al., 2018). This line of research suggests that by some process tags may be separated into a core of tags that are highly central and connected through co-occurrence, and a periphery of tags that are less so. Somewhere between the connected core and the periphery may be the middle ground (or a "semiperiphery", according to Borgatti and Everett, 2000), where tags are not overwhelmingly influential but show some presence. Although these core-periphery models have been widely used to study a wide variety of phenomena in the social science, Gallagher and colleagues (2021) note that different models and operationalizations of core-periphery structure may produce inconsistent descriptions of the structure, and that it is important for researchers to pay close attention to the rich diversity in domain-specific community structures. In the context of tagging, for example, each tag may be thought of as occupying a relative network position to other tags depending on where it falls along any hierarchical core-periphery separation at a point in time. Therefore, although every new tag may start as peripheral, some may gradually occupy more central and/or advantageous network positions due to various structural forces. The formation mechanisms of the core, periphery, and hierarchies of tagging networks is often implied but inadequately tested in the research literature. Hence, we raise the question:

RQ1: How do the core, periphery, and hierarchies of tagging networks emerge over time?

2.2. Functions of tagging: Tags and users' performance

The second part of our theoretical positioning addresses the functional implications for tagging structures and processes. Both the tripartite (users, tags, content) and the core-periphery features suggest that tagging spans multiple levels of analysis. According to Bruns and Burgess (2015), the combined influence and dynamic integration of tags, content, and users serve to assemble and maintain publics around issues, rather than preexisting ties serving as the primary drivers in the assembly of publics. In this assembly process, competing or distracting tags that describe same or similar content often emerge to disrupt the formation of networked publics, but users can coordinate to resolve conflicts by eliminating unwanted variations that undermine the predominance of core tags (Bruns & Burgess, 2015). This kind of community-wide coordination suggests that individuals' tag choices can be driven, in part, by a latent collective mindset.

Although the ability to identify and use core tags that facilitate unified conversations is critical to the maintenance of online publics (e.g., Bruns & Burgess, 2015; Bruns et al., 2016), little is known about how this ability is enacted in online communities. In other words, if an "expert tagger" can leverage tags to sustain networked publics, a fundamental theoretical question is how this expertise should be conceptualized. As noted by organizational communication scholars (e.g., Treem & Leonardi, 2016), expertise is a concept that is notoriously difficult to define. Part of the difficulty originates in the chasm between long-established and contemporary paradigms that view expertise from different perspectives. In classic research (e.g., Collins & Evans, 2007; McDonald & Ackerman, 1998), there is a tendency to theorize expertise as a property of individual experts who possess knowledge and skills that are valued in institutional settings. This conceptualization of expertise suggests that expert taggers find core tags because they possess this ability within themselves to discern the underlying utilities of tags. Recent scholarship (e.g., Fulk, 2016), however, has challenged the assumption of individuality of expertise by hypothesizing that collectives may constitute expertise at a higher-level than individual participants. For example, a transactive memory system (Wegner, 1987), which functions to store group memory in each group member, shows how expertise of individual participants can be aggregated or integrated into expertise that resides in a collective as well as individuals (e.g., Yuan et al., 2010). This alternative view of expertise as a multilevel concept suggests that skillful taggers may find and leverage core tags because they are embedded in an acting collective that facilitates these choices.

Multilevel expertise is particularly relevant in larger social units where individuals are both enabled and restrained by the collectives in which they are embedded (Fulk, 2016). In the context of tagging, individual users play an active part in the development of tagging systems by co-creating and co-selecting tags. However, perhaps none of the individual users has the ability or power to directly designate core tags; rather, the core tags often emerge as a result of collective coordination, meaning creation, or even competition (Bruns et al., 2016). For example, #BlackLivesMatter emerged as a user-selected, unifying tag from many other alternatives (Freelon et al., 2018; Gallagher et al., 2018; Yang, 2016). Thorson et al. (2013) observed the same pattern in the Occupy movement, in which users navigated competing tags and strived to reach consensus and maximize the connectivity among activists. More recently, Petersen and Gerken (2021) examined 28.5 million COVID-19 related tweets and identified over 907,000 unique tags being used; however, only 0.1% of the tags were relatively frequently used (more than 1,000 times) and co-occurred with each other in Twitter communities (60% of the tags were only used once). Through a multilevel theoretical lens (e.g., Kozlowski & Klein, 2000), these examples showcase that the individual users' endeavors to construct and select tags may become emergent properties at the community level, contributing to the formation of multilevel expertise that is possessed and practiced by many users as a whole. In turn, core tags, which are endorsed by the majority of community members and co-occur frequently, become an implicit representation of community norms, organizational climate, and the ecology of collective action (Enli & Simonsen, 2018; Segerberg & Bennett, 2011).

When a user is exposed to content with tags generated by other individuals, the tagging patterns could be observed and assessed, hence internalized or rejected (Halpin et al., 2007; Oh & Monge, 2013). Therefore, tagging decisions may be made based on the user's perception of community climate and other cues available to align tag choices (e.g., On Instagram and Twitter, a user can see how many times a given tag has been used already). Therefore, an individual's expertise of finding the core tags would not exist without the collective action that gives rise to the core tags. In the long run, if individual tagging patterns conform to the shared norms represented by the core tags, users may be rewarded, resulting in better performance, such as more retweets, content likes, video views or better sales of products to which the tags are attached. This somewhat autonomous reinforcement loop may explain the multilevel processes, in which small artifacts like tags can engage and facilitate the formation of larger networked publics. Therefore, we propose the second research question to evaluate how the network structures of tagging proposed in *RQ1* influence performance. This question is critical for the understanding of what makes an "expert tagger", and how the expertise of tagging should be construed:

RQ2: How are network positions of tags associated with their users' performance?

3. Method

3.1. Research context

This study uses data from "Stitchly.com" (a pseudonym), a major e-commerce crowdsourcing community that sells products selected from prototypical designs submitted by users. For each product, the designer can use up to 15 free-form tags, which help users and, ultimately, buyers find the products. The form and rules of tagging activities on Stitchly resemble other mainstream social media platforms. Although the company does not make public its criteria for selecting products, one factor is how highly the product is rated by site users. Stitchly provided us with longitudinal sales data on the tagged products it selected, which can serve as an informative metric to evaluate how different patterns of tag use contribute to performance in the marketplace. The sample used in this research involved 885 designers, who produced 2,785 products that used 8,490 unique tags[2].

3.2. Measures and analysis

Data were obtained and analyzed at three levels: tag, content, and user. For *RQ1*, *k*-core decomposition algorithm was implemented to identify the core-periphery tagging structure at 5 points across a 7-year time period (see "Coreness" section below for details). For *RQ2*, robust regression analyses were conducted separately for the tag, content and user levels to assess the contributing factors to performance. In addition to coreness and performance, a number of other variables described below were input as control variables because they have been identified as relevant to tagging by previous research. Although in many text mining tasks, data pre-processing techniques such as stemming and lemmatization are typically used, the current study did not apply any pre-processing techniques on tags and used all original user-generated tags instead. This is because variations of the same tag or word stem (e.g., #art vs. #artistic vs. #artsy vs. #artsyfartsy) may provide linguistic richness and nuances that would be otherwise obliterated through pre-processing.

3.2.1. Tag-level measures

Coreness. Possessing a high degree is a necessary but not sufficient condition of being core in a network (Borgatti and Everett, 2000; Seidman, 1983), as the latter would require that a tag not only to occur frequently by itself but also co-occur with other core tags[3]. As a computational algorithm to identify core-periphery structures in complex networks, *k*-core decomposition was used to partition the network in nested shells of connectivity and compute the coreness for each tag. Formally, a *k*-core of a graph $G = (V, E)$, where $|V| = n$ vertices and $|E| = e$ edges, is a maximal subgraph $H\ (C, E|C)$ induced by $C \subseteq V$ if $\forall v \in C$, $\mathrm{degree}_H(V) \geq k$ (Alvarez-Hamelin et al., 2006). This suggests that *k*-core decomposition may be a helpful approach for delineating the hierarchical structure of networks and online communities (Chen, Oh, & Chen, 2021).

Performance. To normalize the measure, the performance of a tag was operationalized as the ratio of the total sales revenue of the products where the tag was used to the degrees of the tag in the network. In this way, we could assess how much increase in performance may be partially attributed to the use of a tag. In the sample, the mean performance value of a tag was 45,808.71 US dollars per occurrence ($SD = 69{,}505.57$). As expected, the data were non-normally distributed, with skewness of 4.87 ($SE = 0.23$) and kurtosis of 33.72 ($SE = 0.05$). To reduce the influence of this non-normal distribution on statistical modeling, the data were logarithm-transformed, yielding lower skewness of -0.60 ($SE = 0.23$) and kurtosis of 4.45 ($SE = 0.05$).

Degree. The degree (centrality) of a tag was operationalized as its frequency of occurrence (i.e., the number of times it was used across different products). The average degree for all tags in our sample was 2.75 ($SD = 8.33$), suggesting that a random tag appeared about 3 times on average. The tag "text" had the highest degree, which was 419. However, only 5% ($n = 390$) of the tags appeared more than 10 times in the network. Seventy-one percent of the tags appeared only once ($n = 6{,}030$), indicating that they were never again used after their initial application.

Tag length. Tag length is deemed an important metric in research (e.g., Tsur & Rappoport, 2012). Potentially, longer tags may convey more information, but many platforms often impose restrictions on content length. We quantified tag length as the character count of each tag. The average tag length was 10.14 ($SD = 5.69$).

3.2.2. Content-level measures

Coreness. As a product could use multiple tags, content-level coreness was calculated as the aggregate of the coreness values of all the tags appearing in the same product. Out of the 2,785 products sampled in our research, the average product coreness was 31.55 ($SD = 17.55$).

Performance. Performance at content level was measured by the sales revenue from a product. In the sample, products had an

Table 1
Descriptive statistics and correlations of measures.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Tag-level														
(N = 8,490)														
Perform	–	–	–	–	–									
Coreness	0.04***	–	–	–	–									
Degree	0.02	0.53***	–	–	–									
Length	-0.02	-0.25***	-0.12***	–	–									
Time	-0.17***	-0.38***	-0.22***	0.03***	–									
Content-level														
(N = 2,785)														
Perform						–	–	–	–	–				
Coreness						0.14***	–	–	–	–				
Length						0.12***	0.74***	–	–	–				
Price						-0.03	-0.13***	-0.22***	–	–				
Time						-0.20***	0.08***	0.07***	0.10***	–				
User-level														
(N = 885)														
Perform											–	–	–	–
Coreness											0.10**	–	–	–
Product											0.62***	12***	–	–
Time											-0.15***	0.13***	-0.05	–
M	45808.71	1.68	2.75	10.14	–[a]	43961.77	31.54	69.52	14.53	–[a]	97122.83	31.07	2.18	–[a]
SD	69505.57	1.25	8.33	5.69	–[a]	89710.25	17.55	31.75	9.10	–[a]	189618.64	14.37	3.05	–[a]

Note: $* = p < .05$, $^{**} = p < .01$, $^{***} = p < .001$.
a. The means and standard deviations of time variables are not interpretable and thus not reported in the table.

average revenue of 43,961.77 US dollars (*SD* = 89,710.25). The data were non-normally distributed, with skewness of 8.21 (*SE* = 0.05) and kurtosis of 104.36 (*SE* = 0.09). After logarithm transformation, the skewness was lowered to -0.51 (*SE* = 0.05) and kurtosis to 3.35 (*SE* = 0.09).

Number of tags. On average, the products in the sample used 8.56 tags (*SD* = 4.00).

Tag length. The tag length of a product was quantified as the character count of all tags used in a product. Products in the sample had an average tag length of 69.54 (*SD* = 31.73).

Mean price. Stitchly sells a variety of products using the same design. For example, a graphic can be printed on t-shirts, hoodies, pillows, or coffee mugs, to name a few. Consequently, these products may have different prices, which may have an impact on performance. We calculated the mean price for all the available product types associated with the same prototypical artistic design. Products in our sample were sold at an average price of 14.53 US Dollars (*SD* = 9.10).

3.2.3. User-level measures

Coreness. The user-level coreness was an aggregate coreness value of all the products designed by the same person over time, divided by the number of products. In other words, a designer's coreness in the network was granted by the products that used core tags, controlling for the effect of the designer's productivity. Users had an average coreness score of 31.07 (*SD* = 14.73).

Performance. The performance of designers was an aggregate measure of the sum of sales revenue of all products designed by the same person. Designers generated an average revenue of 97,122.83 US Dollars (*SD* = 189,618.64) in the 7-year period of time. The data exhibited high skewness of 6.68 (*SE* = 0.08) and kurtosis of 68.90 (*SE* = 0.16). After log transformation, the skewness value was lowered to 0.11 (*SE* = 0.08) and kurtosis to only 0.006 (*SE* = 0.16).

Number of products. In our sample, 65.5% of the designers only had one product for sale on Stitchly, in contrast with the top designer who had 38 of them. The median number of products was 1.

Across all three levels, time variables were included as controls. The descriptive statistics and correlations of the variables are shown in Table 1.

4. Results

4.1. Main analysis

RQ1 was proposed to explore how the core, periphery, and hierarchies of tagging networks emerged over time. Results from *k*-core decomposition are visualized in Fig. 1. On June 19, 2006, there were 500 products on the website. The network had a 4-core structure,

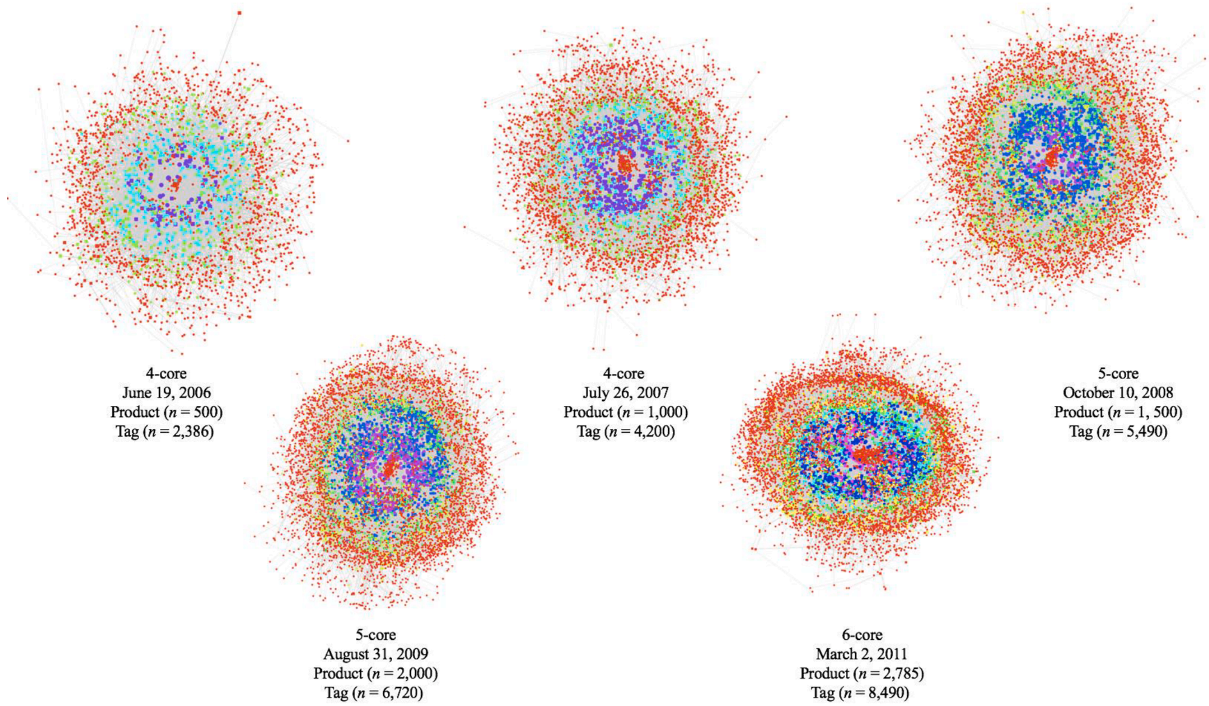

Fig. 1. Formation of core-periphery structure***Note***: A tie is drawn if a tag (round) is used in a product (square) by a user. The visualizations of the core-periphery structure follow the sequence of rainbow spectrum colors (red, orange, yellow, green, blue, indigo, and violet). Red nodes are the most peripheral nodes, and violet nodes are the most core nodes. To better show the network structures, the nodes are sized according to the fourth root of the degree of a node.

with only 62 out of 2,386 tags existing in the very core ($k = 4$). This means that approximately 2.6% of the tags were identified as core tags and were used at least 4 times across different products. Meanwhile, 1,759 out of 2,386 (73.7%) tags were identified as peripheral tags ($k = 1$) that were never used after their initial application. The rest of the tags (23.7%) existed in the space between the core and the periphery ($k = 2$ or 3). The Stitchly community continued to grow at a faster rate, and on July 26, 2007, the number of products doubled. About 5.9% of the tags (249 out of 4,200) were identified as core tags ($k = 4$), 72.7% (3,054 out of 4,200) as peripheral tags ($k = 1$), and 21.4% (897 out of 4,200) in between ($k = 2$ or 3). On October 10, 2008 when another 500 products were added to the websites for sale, the network evolved into a 5-core structure with 5,490 unique tags. In the most connected core of the network, only 83 tags (1.5%) existed ($k = 5$), in contrast with the 3,914 (71.3%) tags on the periphery ($k = 1$) and 1,493 tags (27.2%) in between ($k =$ 2, 3, or 4). Similar trends were detected on August 31, 2009 when a total of 2,000 products using 6,720 unique tags were available. There were 246 tags (3.6%) in the very core ($k = 5$); 4,789 tags (71.3%) were on the periphery ($k = 1$), and 1,685 (25.1%) occupied the space between the core and the periphery ($k = 2$, 3 or 4). On March 2, 2011, the last date that performance data were available, all 2,785 products in our sample produced 8,490 unique tags, resulting in the addition of another nested layer to the core-periphery structure. After seven years of community development and the constant addition of new tags, only 145 out of 8,490 (1.7%) tags became core tags ($k = 6$); 6,038 out of 8,490 tags were not used by people other than the tag creators ($k = 1$). About 17% of tags existed between the core and the periphery ($k = 2$, 3, 4 or 5), which were used to some extent but not extensively.

In line with *RQ1*, *RQ2* explores how network positions (i.e., *k*-cores) of tags influenced their users' performance. Instead of least squares models, M-estimation robust regression (Huber, 1964) was used to address the non-normal distributions of the data. In the models (see Table 2), coreness (across three levels) was entered as the main explanatory variable, and the log-transformed performance (across three levels) was entered as the response variable. Other confounds were controlled for in the models. Multicollinearity diagnosis was also conducted. All variation inflation factors (VIFs) across Models 1, 2, and 3 were smaller than 2.25, indicating that multicollinearity was not an issue that hinders modeling (Dupuis & Victoria-Feser, 2013).

At the tag level where performance was measured as the ratio of the total sales revenue of the products where the tag was used to the degrees of the tag in the network, coreness positively predicted performance, $B = 0.09$, Robust $SE = 0.01$, $p < .001$. Model 1 explained 4% of the total variance in the dependent variable. At the content level, where performance was measured as the sales revenue of the product to which the tag was attached, coreness was also a significant positive predictor of performance, $B = 0.002$, Robust $SE = 0.005$, $p < .001$. The explained variance was 13% in Model 2. At the user level, where performance was measured as an aggregate measure of the sum of sales revenue of all products designed by the same person, the speculation that coreness would contribute to performance still held true, $B = 0.003$, Robust $SE = 0.001$, $p = .02$. Model 3 explained 30% of the variance. A full list of effects and model fit statistics are outlined in Table 2.

Table 2
Results from M−estimation robust regression models.

	Model 1 DV = Ln(Perform) ***Tag-level*** $N = 8{,}490$			**Model 2** DV = Ln(Perform) ***Content-level*** $N = 2{,}785$			**Model 3** DV = Ln(Perform) ***User-level*** $N = 885$		
	B	***SE***	***t***	***B***	***SE***	***t***	***B***	***SE***	***t***
Constant	10.25***	0.03	304.67***	4.37***	0.03	158.86***	4.34***	0.05	85.68***
Tag-level									
Coreness	0.09***	0.01	9.90***						
Degree	-0.00	0.001	-0.52						
Length	0.003	0.002	1.79						
Time	-0.00***	0.00	−16.54***						
Content-level									
Coreness				0.002**	0.00	2.77**			
Length				0.003***	0.00	7.51***			
Price				-0.008*	0.003	−2.50*			
Time				-0.00***	0.00	−7.40***			
User-level									
Coreness							0.003*	0.001	2.41*
Product							0.12***	0.01	11.96***
Time							-0.00***	0.00	−4.86***
F	101.04***			73.98***			68.64***		
R^2	0.04			0.13			0.30		
Root MSE	0.46			0.48			0.47		

Note: * = $p < .05$, ** = $p < .01$, *** = $p < .001$. All "00"s are values smaller than 0.0001.

4.2. Post hoc analysis

To rule out the possibility that the core tags just happened to be the most frequently used words and did not result from collective selection as we postulated, we performed post hoc analysis on the top 200 most frequently used tags in the sample. Specifically, we checked the daily use frequencies of those tags in the English language based on the Corpus of Contemporary American English (Davies, 2012). If a given tag was among the 1,000 most frequently used words, it was considered a core tag *without* linguistic idiosyncrasy (e.g., people, children, food, music, love, cities, cars, buildings, space, movies); if it was not among the 5,000 most frequently used English words, it was considered a core tag *with* linguistic idiosyncrasy (e.g., nerdy, zombies, silhouettes, vinyl, pun, collage, sublimation, pirates, splatter, idioms). Comparisons of the two groups showed core tags with linguistic idiosyncrasies ($n = 64$) contributed to user performance more than those without these features ($n = 52$), $t(87.66) = 2.41$, $p =. 02$, with a medium effect size (Cohen's $d = 0.51$). This result suggests that the collectively selected core tags that performed well were not the frequent words but the unique words. Additional analysis showed that the core tags with linguistic idiosyncrasies appeared much later in the seven year period of life of community, $t(91.58) = 5.52$, $p <.001$, with a very large effect size (Cohen's $d = 1.15$). In general, these results suggest that linguistic idiosyncrasies are associated with higher performance, but the tags with those features may require longer time to take shape in the community.

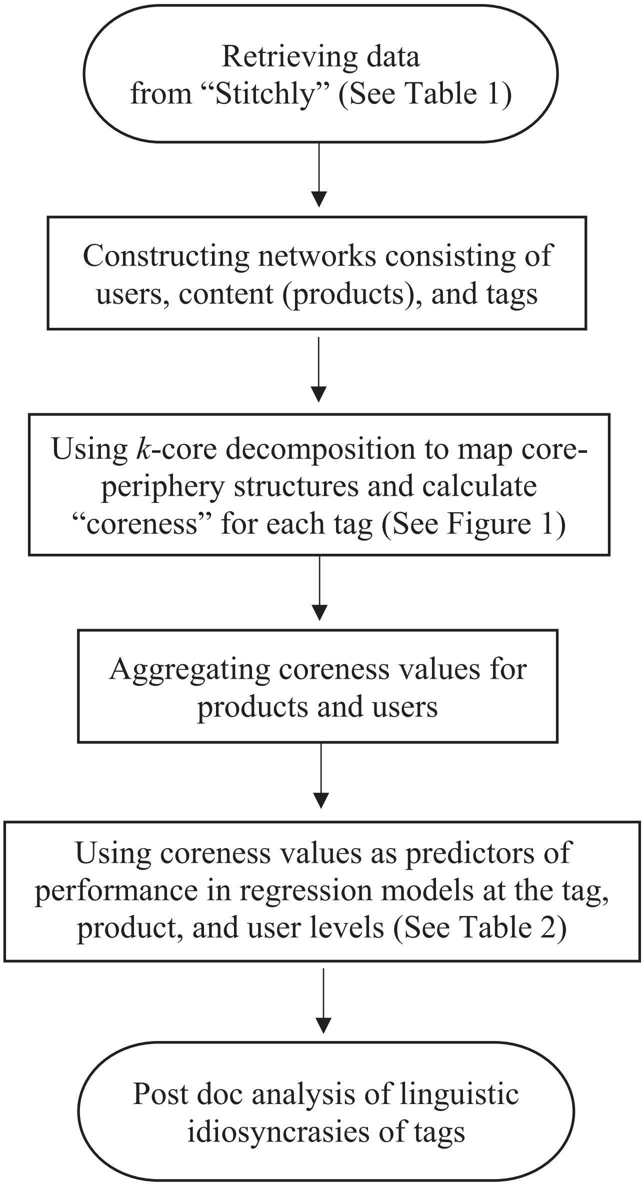

Fig. 2. Flowchart of analytical procedures.

The flowchart in Fig. 2 summarizes the analytical procedures as described in sections 3 and 4.

5. Discussion

Trending and viral tags are regularly being minted and diffusing somewhere on the Internet. Each of them represents a small episode of emergent cultural phenomena, global events, political issues, art genres, among others. What can seem to be individual tag decisions are deeply rooted in an extended social structure, where these tags are both the antecedents and consequences of various networked publics formed around them. Despite the large number of studies that have examined tag use in various media events on numerous platforms, existing literature still lacks systematic and longitudinal accounts of how certain tags become consensus choices and of how tags influence tag users' performance in online communities. To address this gap, the current study presents empirical evidence to demonstrate how tagging structure and functions intertwine. For the structural aspect, this study reinforced recent research (e.g., Petersen & Gerken, 2021) in finding that only a very small number of core tags emerged, even over a relatively long period of time. In line with emergent scholarship on core-periphery structures (e.g., Gallagher et al., 2021), the study showed how a context-specific online tagging system evolved over time. As the structure evolved, higher coreness status demanded more co-occurring tag combinations, from 4 co-occurrences in the early stages to 6 in the later ones. Also, we found that linguistically idiosyncratic tags took more time to evolve, showing up primarily in the later stages of the seven-year window.

Theoretically, the value of the study lies in its capability of revealing the overarching social structure and morphology behind the emergence of certain tags over time as well as their ties to performance. Empirically, the study helps explain how the core tags, which might represent the tacit rules and platform vernaculars co-defined by the community members, improved user performance significantly more than the peripheral tags. The contribution of this study is accentuated by the potential of applying the current theoretical framework and analytical techniques to answer intriguing questions about how tags help establish, maintain, or disrupt networked publics in a variety of contemporary political incidents, social movements, and online memes.

Particularly, the study sheds light on how tags unveil both the collective-level definition and individual-level interpretations of the networked publics, respectively represented by the core and peripheral tags that we sought to differentiate in the study. Hence, the study helps explain how the intangible platform vernaculars emerge from the confluence of individualistic trials as embodied in the tags. In contrast to the common sense that individual users possess certain latitude in creating their own tags, the findings of the study suggest that failing to recognize the consensus choices is detrimental to one's performance.

As previously noted (Papacharissi and de Fatima Oliveira, 2012), tags may help insert users into coordinated spaces where like-minded users can mingle. However, as shown in our study, perhaps most tags do not possess this functionality, considering the massive periphery of the tagging network filled with rarely used tags. Making a core tag in a community is a rare event and could be very time-consuming, and this challenge is especially critical to the evolving understanding of tag-based publics. Perhaps this is why more platforms have realized the importance of providing "recommended" and "suggested" tags to users in order to avoid the low efficiency resulting from complete user autonomy (Tran, Hwang, & Nguyen, 2018). While this top-down approach of directly telling users what the core tags are may be helpful to align users with established publics, it is exposed to the risk of downplaying the importance of peripheral tags and players. After all, while the core may represent unity and power, the periphery may be a place where diversity and distinctness reside, both of which play their unique roles in the complex media ecologies (Bennett et al., 2018; Freelon et al., 2018).

Although a large body of literature has selectively focused on various popular tags, these trending tags may merely represent the tip of the iceberg of the community, where a significant number of users and content expressing the same concern are not connected to these tags. This centralized power structure in tagging systems may be exacerbated by the presence of elites, mass media coverage, and other influential players (Papacharissi and de Fatima Oliveira, 2012). Scholars have sought to address the survivorship bias of trending tags by paying attention to both core and peripheral networks (e.g., Barberá et al., 2015; Bennett et al., 2018). In our study, although using core tags was linked to higher performance, we also noticed that the periphery constantly fed idiosyncratic tags to the community for users to consider. Our finding that linguistically distinctive core tags improved performance corroborates the critical interdependence of the core and the periphery in tagging activities, showing how new norms are negotiated in the long process of community development.

This study also contributes to the growing literature on expertise by conceptualizing expertise as a multilevel phenomenon located in practices as much as in persons. The processes of collective tagging offer an example of how the mutualistic and competitive processes described in the multilevel expertise framework might operate in a collective, such as a networked public. Future work could explore specific interactions more deeply to uncover the nature of cooperative, competitive, symbiotic, and parasitic relationships as proposed in the multilevel expertise framework (e.g., Fulk, 2016) that could develop in tagging networked publics.

Despite the contributions, the study is limited in some respects. First, because users enumerate tags one by one, the first tags may be considered more consequential and would have a stronger effect than those that come after. It is possible that core tags are listed first, followed by peripheral tags. Future research can take into account the effect of tagging sequence that helps delineate how cognitive structures correspond to the network structure of tagging. Second, in the post hoc analysis idiosyncrasies were represented simply by infrequently used words. Future research should examine other types of linguistic idiosyncrasies. For instance, a number of tag-related activist campaigns have employed rich-meaning phrases consisting of plain words (e.g., #MeToo, #NeverAgain). Third, whether the tags accurately describe the content is another important factor in determining tagging intention and performance. Although in this study we did not investigate inconsistent tag-content relationships (e.g., hijacking tags, or exploiting trending but irrelevant tags), future research can apply the analytical framework in other contexts to examine these phenomena. Lastly, all the tags in the Stitchly community were generated by users. This completely bottom-up approach may be different from several social media platforms and online communities where suggested tags, as an important, top-down driving force, serve to calibrate tagging choices. Therefore, although the findings may be to some extent generalizable to other platforms, it is also important for future studies to evaluate how platform-specific features regarding tagging affect the formation mechanisms of core tags and the corresponding effects on user performance. This means that "Who has the power to decide what are the core tags?" would be a meaningful research question that requires further examination.

6. Conclusion

Overall, the study provides an integrated theoretical framework and shows new methodological possibilities for conducting research on the formation mechanisms of tag-based networked publics. As the approach proposed in the study can be applied to track how tags, content, and users co-exist, co-function, and co-evolve in the same ecosystem, future research should examine the larger social systems and institutions where tagging systems are embedded. In this study, although we found that having user-generated content "tagged to the core" contributed to high performance, we also delineated the difficulty and complex contingencies for core tags to emerge. In general, these findings indicate that in order to effectively and strategically manage tag-based networked publics, users and platforms must understand the inherent nature of social tagging systems.

Notes.

1. As not all platforms require "#" (hash) as part of the required tagging syntax, we use the term "tag" to include those that are "hashtags" and those that are not.
2. The products in the sample were made available for sale on Stitchly from November 4, 2004 to March 2, 2011. During the period, a very small percentage of the overall submissions (about 1–3%) was selected as products. Therefore, the sample is a subset of the entire population of the users, content, and tags on the platform, making the potential interdependencies among observations not a major concern.
3. As observed in recent studies of core-periphery structures (e.g., Kojaku & Masuda, 2018), degree by itself might not always be an informative indicator of the importance of nodes. An example of nodes having high degrees but low coreness values is when prolific designers tag all of their products with their names. Their high productivity determines that their names, which are used frequently by themselves, may have high centralities in the network. However, as nobody else may use these tags, they may only form a local cluster instead of connecting to the core of the global tagging network.

Declaration of Competing Interest

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

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