Digital Information Diffusion among Professionals: An Individual-Level Behavioural Approach

Joep van Haren
Maastricht University
Jos Lemmink
Maastricht University, School of Business and Economics
Allard van Riel
UHasselt, Marketing & Strategy
Mahdi Ebrahim
Maastricht University

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Abstract

Professionals increasingly rely on peer-generated content on social media to stay informed about innovations and industry trends, presenting marketers with opportunities to engage professional audiences. Information diffusion on social media occurs mainly through rebroadcasting (i.e., "sharing"). However, it remains unclear what seed selection criteria should be applied in professional contexts. This article empirically examines how information diffuses within professional networks by analysing interdependent, individual-level rebroadcasting behaviours. Using a rich, longitudinal dataset from the X API and Relational Event Modelling, we identify four behavioural mechanisms—engaging, amplifying, mixing, and clustering—that drive diffusion. Our findings, informed by Social Exchange Theory, provide actionable insights for marketers to optimise seeding strategies and enhance content impact in professional networks.

Keywords: Rebroadcasting, Professional networks, Relational Event Model

Track: Digital Marketing & Social Media

1. Introduction

With today's professionals being mostly digital natives (Sinha et al., 2023), professionals increasingly turn to peer-generated content on social media as a cost-effective source of credible information on e.g., innovations, industry developments, and professional knowledge. Consequently, the online diffusion of peer-generated content plays an important role in shaping professionals' attitudes and behaviours presenting marketers with new opportunities to reach professional audiences (Mero et al., 2023). To do so, marketers must devise an effective seeding strategy that identifies suitable "seeds" (i.e., initial targets) whom the marketer can target with their messages (Ameri et al., 2023). However, selecting suitable seeds is a major challenge (Mero et al., 2023) and it is unclear what seed selection criteria should be applied to populations of professionals.

On social media, information spreads primarily through rebroadcasting, i.e., "sharing" (Shi et al., 2014), meaning diffusion relies on individuals' conscious decision to share content. Through the mechanism of rebroadcasting, marketers can reach individuals beyond the immediate vicinity of their company or brand (Lambrecht et al., 2018). Therefore, an effective seeding strategy should identify seeds that have high potential to either engage in rebroadcasting themselves or generate further rebroadcasts for the marketer's content.

Previous research has investigated rebroadcasting behaviour in consumer contexts and identified actor (Lambrecht et al., 2018), content, and network characteristics (Y. Zhang et al., 2017) as drivers of rebroadcasting behaviour. However, professionals have distinctive motivations (compared to consumers) to engage in rebroadcasting (X. Zhang et al., 2017) and thus it remains uncertain whether these factors will influence the rebroadcasting behaviour of professionals.

On social media, rebroadcasting acts are inherently observable by others. Consequently, rebroadcasting acts serve as information cues and create contingencies that govern future rebroadcasting behaviours. Nevertheless, existing research overlooks the interdependencies between individual rebroadcasting acts, assuming these behaviours occur in isolation (Lambrecht et al., 2018; Y. Zhang et al., 2017).

These observations raise interesting questions regarding the seeding strategy for marketers aiming to successfully propagate their digital messages across professional audiences. It is unclear what mechanisms drive rebroadcasting among professionals and thus it is unclear what seed selection criteria marketers should follow. Moreover, given the interdependencies between individual rebroadcasting acts, we do not know how past rebroadcasting acts influence future rebroadcasts. Therefore, this research explores what mechanisms drive rebroadcasting behaviour among professionals, explicitly accounting for the interdependencies between individual rebroadcasting acts.

We conceptualise information diffusion as a process of interdependent, individual-level rebroadcasting behaviours. Each act of rebroadcasting generates information signals and creates contingencies that influence the rebroadcasting behaviours of others, forming a dynamic process embedded in a relational structure involving two classes of interdependent entities, i.e., professionals and content. We represent this as a temporal information diffusion network.

We collected a rich, longitudinal dataset using the X API, capturing time-stamped rebroadcasting events (i.e., "retweets") between professionals and content from multiple medical professional communities. We enrich our dataset with additional actor covariates and employ Relational Event Modelling (REM; Butts, 2008) to analyse our data.

We contribute to the information diffusion literature by expanding the literature to professional contexts. We identify four individual-level behavioural mechanisms – *engaging*, *amplifying*, *mixing*, and *clustering* – that generate the information diffusion network. Drawing on Social Exchange Theory (SET; Shi et al., 2014), we argue that these mechanisms operate based on professional's deliberate choices to rebroadcast content. This perspective remains underexplored in existing literature, which primarily focuses on aggregate-level diffusion reach (Shi et al., 2014) or neglects interdependencies between rebroadcasts (Lambrecht et al., 2018; Y. Zhang et al., 2017).

Practically, our findings offer actionable insights for marketers (and other stakeholders) aiming to propagate information within professional populations. We identify novel individual-level behavioural mechanisms, which marketers can use as seed selection criteria.

2. Literature

2.1 Behavioural mechanisms of rebroadcasting

SET suggest that professionals rebroadcast information as part of a social exchange process, only when the benefits of rebroadcasting information outweigh the incurred costs. Costs involve resources expended or negative outcomes, while benefits include resources gained or positive results (Kankanhalli et al., 2005). In the absence of monetary rewards these may be social rewards, e.g., X. Zhang et al. (2017) find that professionals (vs. consumers) are distinctively motivated to rebroadcast by knowledge self-efficacy – the belief in one's ability to make impactful knowledge contributions (Kankanhalli et al., 2005) – and professional reputation enhancements – how others perceive a professional's image (X. Zhang et al., 2017). Thus, professionals rebroadcast information motivated by knowledge self-efficacy and the anticipation of reputational gains.

Information diffusion engaging is foundational to the information diffusion network. Without professional's active engagement, no diffusion network would exist. Due to biological limits, attention is a scarce resource and professionals can only engage in a limited number of conversations based on their interests and expertise (Lewis, 2021). Therefore, professionals who actively engage (by rebroadcasting frequently) within a community signal their dedication to the community. They may do so because they anticipate reputational gains within this community or because they are convinced that they can meaningfully contribute to this community. Therefore, we hypothesise that active professionals are more likely to rebroadcast content.

H1: Active professionals are more likely to rebroadcast content.

Information diffusion amplifying. Accumulative advantage is a network mechanism in which popularity fosters more popularity, i.e., content that is rebroadcasted often is more likely to be rebroadcasted even more often in the future. When rebroadcasting acts are directly observable, rebroadcasting tends to follow this pattern. Popularity signals intrinsic worth, attractiveness, and appropriateness, serving as social proof (Tonellato et al., 2024). Professionals may see popular content as safe to rebroadcast; since others already rebroadcasted the content there is little risk regarding their reputation to do so too. Therefore, we hypothesise that professionals are more likely to rebroadcast popular content.

H2: Professionals are more likely to rebroadcast popular content.

Information diffusion mixing. While amplifying can drive rebroadcasting, several factors can attenuate it. Popularity may signal an issue's faddish, transitory nature, often leading professionals to ignore it. Additionally, professionals may lose interest in an issue as it gains popularity among others. Disassortative mixing refers to when active professionals rebroadcast unpopular content. We expect disassortative mixing in our network, because the perceived benefits of sharing popular content diminish for active professionals due to its lower marginal impact; anticipated reputation gains decrease when many others already shared the content, and professionals motivated by knowledge self-efficacy may perceive their expertise as redundant. In contrast, sharing less popular content – especially before it gains widespread attention – offers greater marginal benefits in terms of reputation and knowledge self-efficacy for active professionals. Therefore, we hypothesise that active professionals are less likely to rebroadcast popular content.

H3: Active professionals are less likely to rebroadcast popular content.

Information diffusion clustering. Clustering occurs in networks when professionals are indirectly linked to each other through shared interactions with common content, e.g., two professionals rebroadcast the same sets of content. Professionals who share similar beliefs see value in the same sets of content. (i.e., value homophily; McPherson et al., 2001). Therefore these professionals form clusters in the network. We hypothesise that similar professionals are more likely to rebroadcast the same sets of content.

H4: Similar professionals are more likely to rebroadcast the same sets of content.

3. Methodology

3.1 Data

Our dataset captures rebroadcasting acts among healthcare professionals on X. Using the X API, we collected all publicly available tweets from three online medical professional communities ranging from 2017 until 2024. From this data (for each community), we constructed a dynamic, weighted, temporal two-mode network with two node sets: professionals and content. Ties in this network represent rebroadcasting acts, where professional i_e diffuses content m_e at time t_e. Our *information diffusion network* is a sequence of relational events $E = \{e_1, e_2, \dots, e_N)$, with each event taking the form $e_i = (i_e, m_e, t_e)$. Membership in sets I and M is updated at each event time

t_e, as rebroadcasts are only possible once content is created by professionals with active X accounts.

3.2 Model

We follow a modelling approach similar to Shi et al. (2014; Tonellato et al., 2024). Using the Eventnet software (https://github.com/juergenlerner/eventnet), we compute our variables and use the log (+1) transformation to address right-skewness. We then scale these variables around zero to ensure comparability across differing measurement scales. For analysis, we apply a Bayesian Cox proportional hazards model with random effect intercepts. Weakly informative priors were specified for the fixed effects (N(0, 5)) and the standard deviations of the random effects (t(3, 0, 10)) to ensure regularisation. Posterior sampling was conducted using Hamiltonian Markov Chain Monte Carlo with 3 chains, 3000 iterations (1000 warm-up iterations) per chain. Convergence was confirmed with $\hat{R}$ values below 1.01 for all parameters.

Dependent variable. A rebroadcasting event is recorded each time a professional i rebroadcasts a tweet j at time t. Our analysis models the time to the next observed rebroadcast event, conditional on the sequence of prior events. The dependent variable is the probability of observing a rebroadcast event between professional i and tweet j, influenced by actor attributes, dyad attributes, and past interactions. We operationalise rebroadcasting as 'retweeting', the primary rebroadcasting mechanism on X (Shi et al., 2014).

Independent variables. *Information diffusion engagement* (H1) refers to the number of outgoing ties (i.e., out-degree) of a professional. It represents the rebroadcasting acts that a professional engaged it in up until the current time. *Information diffusion amplifying* (H2) is defined as the current number of rebroadcasting acts a tweet has received (i.e., in-degree).

Information diffusion mixing (H3) is operationalised as the interaction between *engaging* and *amplifying*. This variable reflects the decreasing likelihood that active professionals will rebroadcast popular content. *Information diffusion clustering* (H4) is operationalised as an endogenous network effect called bipartite four-cycle, which captures cluster formation in networks.

Control variables. We also include control variables for both professionals and tweets that influence the likelihood of rebroadcasting acts happening, but that we did not create any hypotheses for. For example, we account for connectivity, follower-following ratio, overall tweet activity, tenure, co-location, professionals' inactivity, the number of mentions in a tweet, and finally we include two random intercepts for professionals and content to account for unobserved actor heterogeneity.

4. Results

Table 1. contains the results of our Bayesian Cos regressions for each network. Variables with positive, significant coefficients should be interpreted as increasing the likelihood of observing a rebroadcast event. Variables with negative, significant coefficients should be interpreted as decreasing the likelihood of observing a rebroadcast event.

	#TeleCheckAF	**#DontDistheHis**	**#BLCSM**
Engaging (H1)	**0.07 [0.05, 0.07]**	**0.05 [0.03, 0.07]**	**0.09 [0.08, 0.10]**
Amplifying (H2)	**0.51 [0.50, 0.53]**	**0.37 [0.36, 0.38]**	**0.42 [0.40, 0.43]**
Mixing (H3)	**-0.02 [-0.03, -0.02]**	**-0.06 [-0.06, -0.05]**	**-0.03 [-0.04, -0.02]**
Clustering (H4)	**0.01 [0.01, 0.02]**	**0.10 [0.08, 0.12]**	0.01 [-0.01, 0.02]
Professional Tweet count	**0.16 [0.01, 0.31]**	0.03 [-0.03, 0.09]	**0.35 [0.30, 0.40]**
Content Tweet count	**-0.15 [-0.28, -0.03]**	-0.05 [-0.10, 0.00]	**-0.75 [-0.81, -0.68]**
Professional Tenure	-0.01 [-0.12, 0.09]	**-0.05 [-0.08, -0.01]**	0.01 [-0.03, 0.04]

Content Tenure	-0.05 [-0.10, 0.01]	-0.03 [-0.06, -0.00]	**-0.19 [-0.24, -0.13]**
Professional Followers count	**0.75 [0.27, 1.25]**	**0.22 [0.06, 0.38]**	**-0.27 [-0.39, -0.16]**
Content Followers count	**1.07 [0.18, 1.94]**	0.11 [-0.08, 0.31]	-0.00 [-0.51, 0.52]
Professional Following count	**-0.58 [-1.01, -0.14]**	-0.09 [-0.24, 0.06]	0.05 [-0.03, 0.14]
Content Following count	-0.64 [-1.30, 0.02]	0.02 [-0.21, 0.23]	**0.66 [0.32, 1.00]**
Professional Ff ratio	**-0.60 [-1.05, -0.16]**	-0.02 [-0.15, 0.13]	-0.10 [-0.21, -0.00]
Content Ff ratio	**-0.55 [-1.05, -0.05]**	0.01 [-0.22, 0.23]	**0.55 [0.20, 0.89]**
Professional Inactivity	**-0.36 [-0.43, -0.30]**	**-0.53 [-0.55, -0.50]**	**-0.12 [-0.15, -0.08]**
Content Mentions count	-0.03 [-0.09, 0.05]	-0.01 [-0.04, 0.02]	**0.30 [0.26, 0.34]**
Professional Random intercept	**0.80 [0.71, 0.89]**	**0.69 [0.66, 0.73]**	**0.65 [0.61, 0.69]**
Content Random intercept	**0.44 [0.38, 0.51]**	**0.55 [0.52, 0.58]**	**0.85 [0.80, 0.89]**

Table 1. Results Bayesian Cox regression. Cells contain the posterior mean and [95% credible interval]. Values are log (x+1) transformed and standardised. Values in bold are statistically significant. Variables for 'Professionals' are activity variables and provide information on factors that make it more likely for a professional to rebroadcast content. Variables for 'Content' are preferential attachment variables and provide information on factors that make it more likely that content is rebroadcasted by others.

Overall, we find strong support for all our hypotheses. All variables are significant and have the hypothesised direction in each network, except for *clustering* which is insignificant in #BLCSM. In support of Hypothesis 1, we find that *engaging* has a positive effect on the likelihood of observing a rebroadcast event. In support of hypothesis 2, we find that content that has been rebroadcasted more often in the past, is more likely to be rebroadcasted again in the future. In support of Hypothesis 3, we find that professional's rebroadcasting activity level within a community mitigates the positive effect of *amplifying*. Finally, in support of Hypothesis 4 we find that similar professionals tend to rebroadcast the same set of content.

5. Discussion

To diffuse information across a population, marketers must devise effective seeding strategies. Understanding which mechanisms drive rebroadcasting behaviour is key for doing so. Seeding strategies should be informed by those factors that increase rebroadcasting activity. While the mechanisms of rebroadcasting behaviour have been studied in consumer contests (Lambrecht et al., 2018; Y. Zhang et al., 2017), research in professional settings is lacking.

In this article we study what mechanisms drive rebroadcasting behaviour among professionals, accounting for the interdependencies between individual rebroadcasting acts. We find evidence that supports our hypotheses. *Engaging* (H1), *amplifying* (H2), and *clustering* (H4) positively influence the probability of rebroadcasts occurring. *Mixing* (H3) mitigates the positive effect of *amplifying*.

5.1 Contributions

We contribute to the literature on information diffusion in several ways. First, we extend the literature on information diffusion to professional settings by studying what mechanisms drive rebroadcasting behaviour among professionals. Second, we contribute to the literature on rebroadcasting behaviour, which studies this activity in consumer contexts and neglects the interdependencies between individual acts of rebroadcasting. While accounting for these interdependencies, we identify four individual-level behavioural mechanisms driving rebroadcasting behaviour among professionals.

Marketing practitioners may use our results to guide their seeding strategies based on our behavioural selection criteria. New content should be targeted at highly active professionals and marketers should leverage the natural closure of clusters within the network. Marketers should monitor professionals rebroadcasting behaviour to uncover open three-paths connecting a professional (indirectly) to content. By targeting this professional with the content s/he is indirectly connected through, via e.g., a mention, marketers can boost the natural closure of clusters and stimulate rebroadcasting.

Our research is not without limitations. Although we study various networks of different types of healthcare professionals, our results are limited to healthcare professionals. Many other kinds of professionals use social media for professional information exchanges, such as e.g., farmers. although our research identified mechanisms driving rebroadcasting behaviour, we did not test what the most effective seeding strategy is. Future research could use simulations and field experiments to determine the optimal seeding strategy for maximising rebroadcasting activity.

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