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Network's reciprocity: a key determinant of information diffusion over Twitter

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ABSTRACT

The role of social media, particularly Twitter, in ensuring the large-scale propagation of information cannot be overemphasised. This study introduces the recipient network's reciprocity toward a particular topic as a novel factor that contributes toward a central node's information propagation potential, in addition to other widely studied factors. It first employs multiple regression analysis to present a model that reveals the prominent roles played by both content popularity, focal ratio, engagement efforts of users, and the recipient network's reciprocity toward a topic, in determining his or her propagation potential. Further, it investigates the impact of the interaction terms of each of these propagation dimensions and the network's reciprocity toward the topic on a user's propagation potential. The results show that the network's reciprocity toward the topic (i.e. 'blockchain' in this study) is important for modelling the diffusion process accurately. Second, applying a multi-methods approach, this study also incorporates fuzzy set qualitative comparative analysis (fsQCA). It reveals four alternative combinations of explanatory variables (propagation dimensions) that are sufficient for achieving the expected outcome (propagation potential of the user/central node). The study found fsQCA results complementing the results of the regression model.

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Information propagation; reciprocity; regression; fsQCA; Twitter; blockchain

1. Introduction

Social media refers to interactive platforms generated by mobile- and web-based technologies that facilitate information sharing and co-creation (McLean, Richards, and Wardman 2007) through discussions and modifications of user-generated content by individuals and communities (Scott and Orlikowski 2014). Unlike information propagation in traditional media, it has been observed that information propagation on social media platforms appears at a larger scale, is multi-mode, real-time, and rapid (Donghao and Wenbao 2014). The uniqueness of social media lies in its flexible and broad-based architecture that empowers individuals and communities to effectively communicate around their common interests and, in the process, extend social interaction and information exchange.

Existing studies on information diffusion have focused on identifying the central nodes that could contribute toward diffusion (Abubakre, Ravishankar, and Coombs 2015). The presence and forwarding behaviour of high-impact nodes is observed as the key factor in stimulating information propagation at a larger scale, especially in the case of propagation of information about new technology (i.e. blockchain in this study). Further, a significant amount of attention has been directed toward understanding the important factors that enhance the capability of users or central nodes toward information propagation. Previous studies support the belief that the most socially influential person is the most connected person, i.e. one who has many followers (Alp and Öğüdücü 2018). Various studies have further revealed that successful propagation of a message in social media depends significantly on the relevance of content (Shi et al. 2018), closeness of social relationships (Li and Shiu 2012), and users' activities (Yu, Chen, and Ran 2016). These studies examine the information propagation process from a sender's perspective.

Complementing this perspective, another stream of research examines the information propagation process from a recipient's perspective. It posits that, in such platforms, the followers of a central node actively participate in value co-creation practices (e.g. sharing their knowledge, ideas, and preference information) to support and collaborate with the central node. Given that network users are now active co-producers of value and meaning (Kozinets et al. 2010), their information exchange behaviour becomes a crucial aspect

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to be investigated as it can inform the emotions, opinions, and actions of the public. Thus, the core to successful management of information propagation is understanding what stimulates followers' sharing behaviour on Twitter. Existing research identifies the factors that influence the behaviour of network users in terms of extending the propagation via retweeting, sharing, or mentioning opinions or content. Delving into the motivations of the users for such behaviour, studies (Starbird and Palen 2010) have revealed that people spread information through retweeting, mostly when they know or feel it to be newsworthy. In their study, Liu, Liu, and Li (2012) applied the heuristic-systematic model of information processing and revealed the impact of both heuristic and systematic factors on recipients' behaviour in a network.

However, previous studies have not examined an integrated model that combines the aforementioned streams and incorporates the role played by the recipient network in determining the success of a particular central node in propagating information. Although few existing studies incorporate factors such as the audience's sentiment in assessing the information propagation potential of central nodes (Arora et al. 2019), studies have indicated the need to integrate novel network metrics such as reciprocity to generate useful insights for information propagation by central nodes on various platforms (Arora et al. 2019). The current study investigates the role of the network's reciprocity toward a particular topic in the overall success of the central node, as it seems logical that a more collaborative and engaging response from the network should contribute to the propagation potential of the node. Specifically, we posit that the increased reciprocity of the user's network for a particular topic (blockchain technology in this case) results in enhanced conscious engagement in collaborative activities. This would further increase the network's contribution toward discovering and spreading new knowledge emanating from the central node, thereby augmenting its social influence. Further, the impacts of the central nod's network structure, its content popularity, its focal ratio (the degree of topic-specific content posted), and its engagement efforts (as defined by the number of tweets, retweets, and favourites on the topic by it) on its information propagation success is tested. Additionally, previous research has indicated that information diffusion can be contingent upon sentiment valence (Ma, Sun, and Kekre 2015; Stieglitz and Dang-Xuan 2011). Therefore, to disregard any confusion and exclude clarifications, we considered the central node's sentiment valence (ratio of the number of positive tweets on the topic to total tweets on the topic) as a control variable in the current study. Thus, we study a diffusion model that considers the popularity of users' content, focal ratio, structure, engagement efforts of the user, and reciprocity of the users' network toward the topic, as the essential ingredients for successful information propagation by the central nodes.

We study information diffusion in the context of 'blockchain' the distributed-ledger technology, majorly led by various players, such as financial services and consulting firms (Miles 2017), specifically on microblogging platform Twitter, where users primarily decide on what is valuable through the diffusion mechanism. Blockchain is an IT innovation at an early stage of diffusion, but has shown the potential to disrupt IT, financial services, and many other industries and generate significant benefits for the overall economy (Lynn, Rosati, and Fox 2018). Given that it is still at a nascent stage of development, various organisations seek to reduce the related uncertainty (Albrecht, Lutz, and Neumann 2019) and legitimize blockchain (Lynn, Rosati, and Fox 2018), mostly by leveraging social media. This is primarily because social media creates public forums that facilitate interactions between multiple audiences (Marwick 2011). The extant literature on information diffusion can also provide insights into the predictors of adoption/propagation for many technologies, especially those in the nascent stage, and seek legitimisation. However, such an approach has not been explored sufficiently in blockchain, and the current study fills this gap.

Methodologically, this study adopts a multi-method approach and employs multiple regression analysis (MRA) and fuzzy set qualitative comparative analysis (fsQCA) (Ragin 2009) to complement the analysis made possible by both techniques. This approach enables us to compare correlational and set-theoretical methods. Although employing regression helps us identify relevant conditions for successful information propagation, it does not indicate whether the conditions provide alternative paths to success (equifinality) or are part of a single path (conjunction). A set-theoretical approach seems quite relevant here. Thus, this study adopts a multi-method approach, employing both set-theoretical and correlational (hypothesis testing) approaches.

The MRA models are used to assess the net effects of central node's structure, content popularity, focal ratio, engagement efforts and network's topical reciprocity on the information propagation potential of the central node as well as to predict the moderating role played by the network's topical reciprocity on the relationships between the central node related factors and its propagation potential. Given the growing importance of collaborative engagement on Twitter as a communication platform and the strategic importance of co-creating an information flow, such a model should be useful for both practitioners and researchers in the domain of 'blockchain technology.' The other method, fsQCA, was selected because despite that information diffusion is primarily multidimensional, less is known about the possible interdependencies of the propagation dimensions and how ensuing configurations of those may relate to various levels of propagation. Specifically, while prior studies consider the net effects of individual information propagation dimensions, the impact on the propagation potential of the central handle, based on their interdependencies, remains unclear. In addition, distinct configurations that capture both the network's reciprocity toward the technology and the central node's propagation dimensions on Twitter may affect the propagation potential of the central node. Existing research is silent on such interdependencies and configurational logic. Thus, the value of fsQCA approach lies in its ability to capture combinatorial complexities, assuming asymmetrical relationships between variables, rather than the symmetrical net effects that regression considers. The fsQCA results complement the regression model results in that they reaffirm the important role of the recipient network's reciprocity in the propagation of information about 'blockchain' on Twitter.

The study has the following multi-fold contributions. The proposed approach integrates the central node-related factors such as content popularity, the focal ratio, the network structure, user/node's engagement initiatives, and recipient-related factors (i.e. the network's reciprocity toward a particular topic; blockchain in this study) to assess the propagation potential of the central node. We also studied the moderating role played by the network's topical reciprocity on the relationships between the central node related factors and its propagation potential The varying impact of content popularity, focal ratio, and engagement efforts on the overall propagation potential of the central node in the presence of high reciprocity to the topic provides some interesting insights.

Existing papers in the field are dominated by the general net effect thinking. The influence of individual variables is ascertained, or the interaction effect of the two variables is sometimes conceptualised as a moderator model. However, in reality, it may be a combination of several factors that lead to certain outcomes. This study supports the notion that different information propagation configurations exist, and these are characterised by differences in the propagation dimensions. Thus, several possible pathways (configurations of information propagation dimensions in consideration of the network's reciprocity toward the technology) lead to a high propagation potential of the central node. Accordingly, the impact of information propagation dimensions is interdependent, and all the lower-order configurations are conditional on the network's reciprocity toward the topic, representing the conditional impact of the same on the propagation potential of the central node. Thus, this study makes an important contribution to our understanding of information diffusion/propagation in social media platforms by demonstrating that conditional configurations of diffusion/propagation dimensions exist that have an equal impact on the propagation potential of the central node.

This study is relevant for practitioners such as organisations and individuals (mostly in media, financial services, consulting, IT) as they attempt to leverage social media to reduce the uncertainties related to the technology. Although understanding and building on the popular content, topical focus, and engagement efforts by the central node remain prerequisites for information diffusion success of the node, on Twitter, the role played by network reciprocity in enhancing the user's influence cannot be undermined. Thus, listening to and observing the reciprocity of the network in relation to a particular topic and strategizing accordingly would enhance the node's propagation potential.

The remainder of this paper proceeds as follows. Section 2 uses an interdisciplinary approach to synthesise the related literature across marketing and information systems domains with specific attention given to information propagation dimensions and their interrelationship with the propagation potential of a central node within Twitter. Section 3 develops conceptual arguments for the empirical assessment. Sections 4 and 5 present the methodology, analysis, and results. Finally, the implications of the theoretical and practical results are discussed in Section 6, and the conclusion is presented in Section 7.

2. Literature review

2.1. Twitter

Twitter, one of the most popular microblogging social media networks, offers functionalities such as tweets (a message limited to 280 characters), hashtags, @messages, retweets, and follower relations (Kayser and Bierwisch 2016), among others. Over the years, Twitter has become indispensable for spreading information related to personal as well as professional and political contexts. The platform is being increasingly used by businesses, politicians, and governments to reach consumers and citizens, respectively (Kayser and Bierwisch 2016). Existing studies (Wigand 2010; Van De Velde, Meijer, and Homburg 2015) suggest that Twitter can help organisations to share essential information with the public and induce them to participate in new initiatives. Thus, it emerges as a social system with information-sharing functions, reflected in broadcasting behaviours and conversations among users on topics of mutual interest, making it an ideal candidate for studying social exchanges in social systems (Shi, Rui, and Whinston 2014). This is all the more applicable to topics on new technologies such as blockchain (Tempini 2017; Grover, Kar, and Janssen 2019). In addition, social media (Twitter) has been widely considered as the chosen platform for the study of information propagation because it is a valuable source of voluntary information disclosure (Lischke and Fabian 2016) and because online conversations are easy and cost-effective ways to measure word of mouth (Godes and Mayzlin 2004).

2.2. Information diffusion on twitter: social exchange theory

Extensive research has been conducted on online social networks to investigate the context of information diffusion (Suh et al. 2010; Stieglitz and Dang-Xuan 2012). Information diffusion-related research applies techniques such as social network analysis to identify the powerful nodes that play a crucial role in the diffusion of information (Abubakre, Ravishankar, and Coombs 2015; Cho, Hwang, and Lee 2012). User influence has been explored using multiple lenses. Research has brought forth a variety of social media user influence measurement models based on various algorithms (Arora et al. 2019). (Weng et al. 2010) proposed the Twitter-Rank algorithm, which calculates the influence of the user by taking into Twitter's following structure and user interest similarity. (Pal and Counts 2011) computed an individual's spreading influence, forwarding influence, and mentioning influence based on the number of fans, posts, replies, forwarding, and mentioning from Twitter's database, respectively. Similarly, study by Meeyoung et al. (2010) compared the different measures of user influence on Twitter and suggested using the number of followers, retweets, and mentions. Kwak et al. (2010) utilised the number of followers, retweets, and PageRank in the follower's network, with similar comparison results between user ranks.

In conjunction with the aforementioned studies with a sender's perspective, another stream of research examined the information propagation process through a recipient's lens. Shi et al. (2018) applied the elaboration likelihood model and reiterated the positive impacts of the factors of both the central and peripheral routes on individual dissemination behaviour. Studies that consider the recipient's perspective identify the factors that influence the recipients' behaviour for extending the propagation via retweeting, sharing, or mentioning opinions or content. Extant literature emphasises on the motivations of users for such behaviour. People spread information through retweeting, mostly when they know or feel it is newsworthy (Starbird and Palen 2010). Liu, Liu, and Li (2012) applied the HSM theory and revealed the impact of both heuristic and systematic factors on the behaviour of the recipients. The heuristic factors considered (i.e. user trustworthiness, attractiveness, and expertise) were found to significantly impact information retweeting. Furthermore, all the systematic factors considered (i.e. content accessibility and vividness) were found to influence information retweeting.

Despite the aforementioned extensive research, an integrated model that combines the two streams and incorporates the role played by the recipient network in determining the user's/central nodes' information propagation success is less examined. Few recent studies have examined the interests of users in different types of information and demonstrated that incorporating specific users' interests could enhance the performance of predicting the scale of information propagation (Hoang and Lim 2016). Similarly, we posit that a network's reciprocity toward a particular topic becomes crucial in deciding the overall success of the central node. We use the lens of social exchange theory to guide this proposition. Existing studies suggest that, owing to the content-sharing nature of information propagation on social media, social exchange theory is an appropriate lens to explain observations (Li et al. 2018). Social exchange theory maintains that relationship decisions are based on the outcomes of social behaviours (Blau 1964) and social media users' online social behaviours (e.g. information propagation) are typical social exchange behaviours associated with a variety of outcomes, including a sense of belonging, reputation, self-esteem, feeling of obligation, altruism, and reciprocity (Ngai, Tao, and Moon 2015; Shi, Rui, and Whinston 2014).

2.3. Network's reciprocity towards the topic

(Nowak 2006) proposed five mechanisms associated with the evolution of cooperation, kin selection, direct reciprocity, indirect reciprocity, network reciprocity, and group selection. (Faraj and Johnson 2011) built on the five mechanisms and revealed that direct and indirect reciprocity are the core patterns of online communities. In the context of Twitter, one may infer that activities such as retweets, favourites, and tweets, with respect to a particular topic, also demonstrate the reciprocity characteristic. These activities are designed to indicate both direct and indirect reciprocity by directly pointing to someone and by enabling asymmetric interactions. We adopted the lens of the network's reciprocity toward the topic. We look through the lens of a specific topic (in this case, the drive to propagate information on 'blockchain' by the network users). It is assumed that co-operators form network clusters when it comes to a particular topic and here they help each other by utilising the aforementioned activities.

2.4. Role of network's reciprocity in information diffusion

An existing study (Chiu, Hsu, and Wang 2006) has demonstrated that the norm of reciprocity and community-related outcome expectations can significantly affect the quality of knowledge sharing. Some studies (Chang and Chuang 2011), (Chiu, Hsu, and Wang 2006; Schumann, Wangenheim, and Groene 2014) asserted that the reciprocity norms have positive effects on members' information-sharing behaviour, even in anonymous settings such as internet browsing. The current study examines how the usage of retweets, mentions, and favourites activities (as a reflection of reciprocal behaviour) can contribute to building social capital for a topic trending on Twitter and simultaneously influence the information propagation potential of the central node.

In other words, we posit that the topical cohesion among network users is important because users in the network would reciprocate differently to varied topics, impacting the dissemination of the information. Other studies (Gadek et al. 2018) have indicated that existing communities on SNSs are topically dependent and detecting them requires an appreciation of not only the relations between users but also the topic of exchanged messages. This implies that the network's users who are actively reciprocating on a particular topic will be more approving of a user's topic-specific initiatives/efforts and would exhibit engaged/reciprocal behaviour in the context of the user, in the process of expanding social capital. Thus, the outcome of information propagation from a user/node depends on the motivated and reciprocal network users. Thus, the inclusion of network reciprocity as a construct enables the examination of the network's contribution toward enhancing the information propagation capabilities of an individual user.

The information diffusion model is studied by considering the ingredients essential to successful information propagation by a user. These ingredients are content popularity (number of high-frequency topic-related words by the user), focal ratio (the degree of topic-specific content), structure (user's followers), engagement efforts of the user on the topic (the number of tweets, retweets, and favourites on the TOPIC by the user), and reciprocity of the users' network toward a particular topic (retweets, favourites, tweets on a topic by the network).

3. Model development

3.1. Effects of structure

The number of ties in a social network is a well-established measure of the individual-level influence for a specific network (Goldenberg et al. 2009; Stephen and Toubia 2010; Arora et al. 2019). Given the way people connect with each other in SNSs, a user with a high degree of interpersonal influence can attract many people. For immediate and larger collaborative diffusion of creative content, it is essential that central nodes have more network ties because it would enable them to not only ensure dissemination of a wide range of information but also to create new knowledge. Thus, the propagation success of a node is positively impacted by network connectivity; therefore, we hypothesise the following:

> H1. Network connectivity on Twitter has a positive impact on the propagation success of the user/central node.

3.2. Effects of content

Content popularity: Previous studies have explored content from different dimensions, such as the appropriate amount of information (Chen, Tseng, and Liang 2010), volume, and diagnosticity. Existing literature (Li and Shiu 2012) suggests that message propagation in social media depends greatly on content popularity. Users with high content popularity imply that they are influential, as users become attention-grabbing when they are responded to by others. Cha et al. (2010) indicate that the content value of one's posts is an important measure for evaluating influence. Content popularity has been previously defined as the similarity between a user's content and high-frequency keywords appearing in tweets on the Twitter platform (Li and Shiu 2012). We build on these studies and emphasise the contribution of content popularity toward expanding social capital and adding to the social influence of a user in the context of a specific topic. Thus, we hypothesise the following:

> H2.1. The popularity of content in a message has a positive effect on the propagation success of the user/central node.

Focal ratio: The existing literature suggests that users' topical focus results in a higher influence compared to users' dealing with several topics (Alp and Öğüdücü 2018). The focal ratio was operationalised as the number of tweets on the topic by the user divided by the total number of tweets on Twitter. A similar feature was previously used by (Pal and Counts 2011)as 'Topical Signal' Drawing from these studies, we posit that the more focused the user is on a particular topic, the greater the depth of information and the greater the impact on the user's overall influence. Therefore, when measuring a user's influence, we emphasise his or her focused contribution toward furthering social capital in the context of a specific topic. Hence, we can hypothesise the following:

> H2.2. The focal ratio of the user has a positive impact on the user's/central node's propagation success.

3.3. Effects of engagement efforts

User influence has been found to be highly correlated with user activity mapped in temporal terms (Yu, Chen, and Ran 2016). Existing studies further document the role of the frequency of posts. Engagement is an activity-oriented measure that accounts for the efforts made to be influential. Drawing from previous studies (Alp and Öğüdücü 2018), we operationalise it as the total number of tweets, retweets, and favourites on a specific topic by the user. The dimension succinctly displays continuous engagement efforts toward building social capital from the user or the central node. Drawing from previous studies, we hypothesise the following:

> H 2.3: The level of engagement of the user on Twitter has a positive impact on the propagation success of the user/central node.

3.4. Effects of reciprocity

In the online context, tangible elements may be less salient, so the norm of reciprocity can be an important 'push factor' that shapes the information-sharing nature of members (Wiertz and de Ruyter 2007; Wasko and Faraj 2005). Existing studies have indicated the need to integrate novel network metrics, such as reciprocity, to generate useful insights in terms of information propagation on the social network of central nodes on various platforms (Aswani et al. 2018b; Arora et al. 2019). Considering the studies examined above, our focus is on examining the usage of retweets, mentions, and like activities, by the network, as a reflection of the reciprocal behaviour toward a topic, and on analysing the contribution of these activities to build social capital further, and simultaneously enhancing the information propagation potential of a user. Thus, we propose the following hypothesis:

> H3. The reciprocity of the network toward a particular topic (blockchain in this study) has a positive impact on the propagation success of a user/central node.

3.5. Moderating effects

Existing studies identify the influence of content popularity in extending propagation and indicate that people spread only the information they feel or know to be newsworthy through retweeting (Starbird and Palen 2010). Therefore, we posit that the higher the reciprocal characteristic of the network toward the topic the central node is delving in, the greater the synergy between the central node and his or her network, resulting in enhancing the information propagation potential of the central node. Hence, the reciprocity of the network toward the topic accentuates the influence of content popularity on the propagation success of the user. Thus, we hypothesise the following:

> H4: The effect of the popularity of content in a message on the propagation success of the user/central node is accentuated in the presence of high network reciprocity.

Existing studies indicate that the topical focus of a user, rather than his or her dealing with several topics, results in a higher influence (Alp and Öğüdücü 2018). We posit that the higher the reciprocal characteristic of the network toward the topic the user is focusing on, the greater the topical coherence between the central node and his or her network, enhancing the information propagation of the central node. Thus, we hypothesise the following:

> H5: The effect of the focal ratio on the propagation success of the central node is accentuated in the presence of high network reciprocity.

Engagement displays continuous efforts toward building social capital from the central node's end. Therefore, we posited that the higher the reciprocal characteristic of the network toward the topic, the higher the effort from both the directions (network and the user/central node), enhancing the information propagation of the central node.

H6: The effect of engagement efforts by a central node on his or her propagation success is accentuated in the presence of high network reciprocity.

Further, many studies have investigated some of the above possible antecedents of information propagation (i.e. network connectivity, popularity of content, focal ratio, and level of engagement) in isolation. In this study, these factors are examined together with the network's reciprocity to understand how different combinations of these antecedents lead to information propagation. It is possible that different antecedents in a combination can negatively or positively impact the outcome variable, depending on the absence or presence of other elements in the combination (Woodside 2013). Additionally, relationships between variables can be non-linear, with discontinuities manifested at different levels. Thus, we investigated the following:

Research Proposition: Disparate configurations of network connectivity, the popularity of the content, focal ratio, level of engagement, and reciprocity are equifinal, leading to high information propagation.

4. Research methodology

4.1. Data collection

The data for this study were collected from Twitter, which were retrieved through the Twitter web application programming interfaces (APIs). The unit of analysis in our study was a Twitter user. The terms user, central node, account, and central handle (CH) are used interchangeably in this study. The public stream endpoint offered by Twitter APIs was monitored during the first week of August 2019. Tweets with the keyword #Blockchain were used to identify the users that generated content on blockchain on Twitter. In the collected tweets, high-frequency words, as shown in Figure 1, were obtained to measure the content popularity of the central handles. Furthermore, the set of high-frequency keywords related to #Blockchain, such as cryptocurrency, crypto, and bitcoin, denoted as TOPIC, are used to calculate the reciprocity of the network. The tweets of the central handles and their networks were observed during August 2019. This is denoted as OBSERVATION_PERIOD.

The tweets' language code was checked, and only the tweets in the English language were retained for further analysis. This resulted in the collection of 50,000 tweets and retweets, which were made by 20,992 handles. Moreover, the profiles for which there were no retweets of their tweets were eliminated, resulting in 14 270 accounts. Because the Twitter API does not allow us to obtain the information of the protected profiles, such accounts were eliminated. From the resultant dataset, a sample of 371 observations was obtained. Extant research suggests that the sample size is sufficient to capture medium effect size in regression analysis (Green 1991). Subsequently, the Twitter REST API was used to retrieve the followers' list and all the tweets, retweets, and favourites made by these accounts.

To calculate the reciprocity of the handle's network, the tweets, retweets, and favourites of their followers—in total, data from 65,628 accounts—were also extracted. As shown in Figure 2, a network of central handle followers typically consists of some inactive (IF) and active followers (AF). In our study, followers who tweeted or retweeted on any topic during the observation period were considered as active users. Among

Figure 1. Word cloud from tweets related to blockchain.

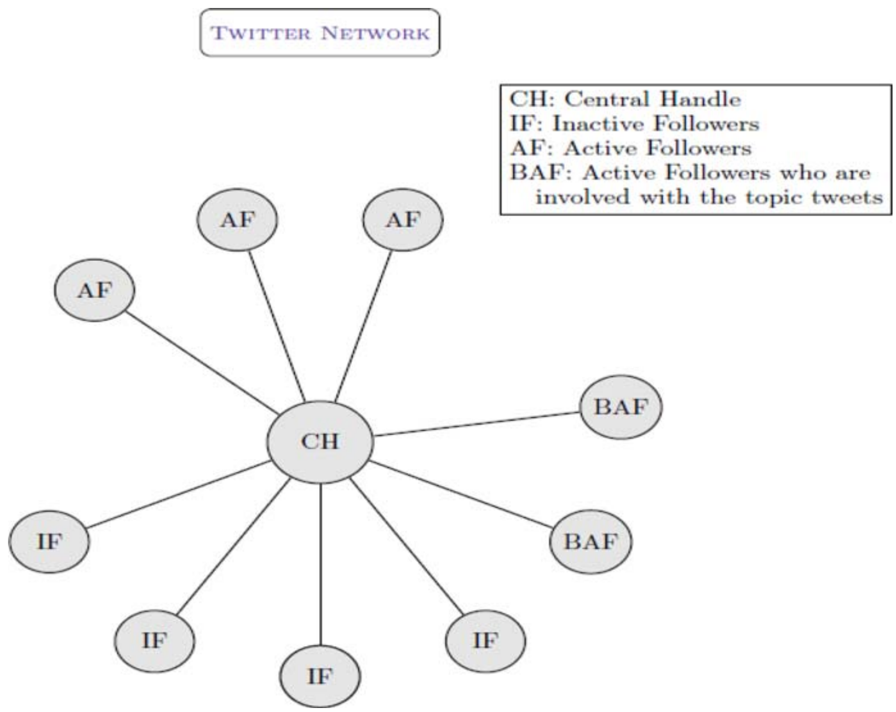


Figure 2. Example of a Twitter network.

the active followers, some actively participated in blockchain's topic, which is denoted as blockchain active followers (BAFs). The minimum and maximum number of followers in the sample were 94 and 3634, respectively. Further, on average, out of a user's active followers, only 48% showed some activity related to blockchain. To ascertain the reciprocity of a central handle's network, their followers' accounts were scanned for their tweets, retweets, and favourites on TOPIC. Step-wise data extraction is listed in Table 1.

4.2. Operationalisation of variables

Y_prop is defined as the total number of retweets and favourites generated by the central handle (CH). Although the retweets are distinct from the favourites, both are considered to measure the success of propagation.

Table 1. Step-wise data extraction.

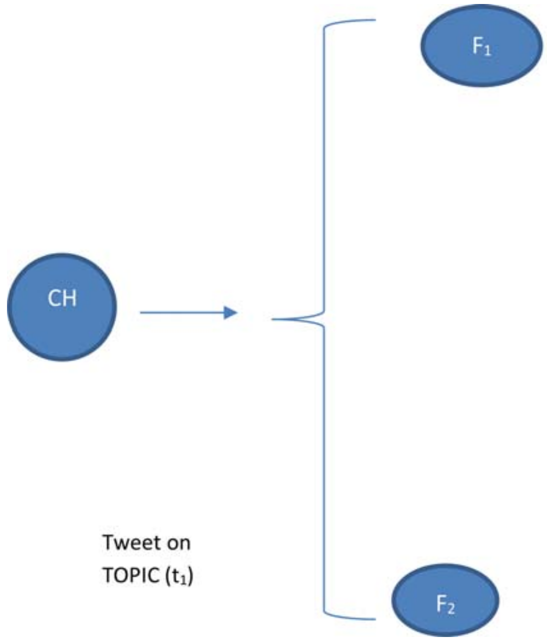
		Data points
Step -1	Extracting all tweets with the hashtag Blockchain from Twitter in the first week of August 2019 and denoted as Tweets_Corpus.	50,000 tweets
Step-2	Identification of handles who authored the tweets	20,992 handles
Step-3	Downloaded the profile information of all 20,992 handles	
Step-4	Remove the protected or deleted accounts	
Step-5	For 371 handles and their followers, downloaded tweets, retweets, and favourites in OBSERVATION_PERIOD	65,628 accounts, 15,556,866 number of tweets, retweets, and favourites

Cval is defined as the content popularity of tweets made by the central handle (Li, Lai, and Lin 2016). The tweets (Tweets_Corpus) were collected with the keyword 'blockchain' on the Twitter timeline. The 'Tweets_Corpus' is processed to extract keywords with high frequency (TOPIC). These words encapsulate the contents of tweets that are in circulation on Twitter. For each central handle, the tweets posted on the TOPIC in the OBSERVATION_PERIOD are gathered and cleaned by removing stopwords, URLs, etc. The Cval of a CH is measured by the number of frequently used terms (TOPIC) in the tweets made by the CH.

Sentiment valence of a CH is measured based on the positive and negative tweets about TOPIC. In the literature, various Twitter sentiment valence measurements have been used (Ma, Sun, and Kekre 2015; Stieglitz and Dang-Xuan 2011). In our work, the sentiment valence of a central handle is defined as the number of positive tweets on TOPIC divided by the total number of tweets on TOPIC.

Focal Ratio: This feature calculates the intensity of the tweets of a user on a specific topic. It is defined as the total number of tweets for TOPIC in OBSERVATION_PERIOD divided by the total number of tweets on any topic (Alp and Öğüdücü 2018; Pal and Counts 2011).

Engagement: Following (Alp and Öğüdücü 2018), the engagement efforts of the central node are measured



	TOPIC related actions of F_1 & F_2	Component
1	Number of retweets and favorites of t_1 by F_1 & F_2 and their followers and so on	Y_prop
2	Number of tweets on TOPIC made by F_1 & F_2	Reciprocity
3	Number of retweets and favorites on TOPIC made by F_1 & F_2	Reciprocity

Figure 3. Reciprocity of central handle's network.

as the total number of tweets, retweets, and favourites on TOPIC by CH in OBSERVATION_PERIOD.

Structure: Structure is defined as the number of followers of the central handle.

Reciprocity: The reciprocity of the central node's network is defined as the sum of the number of tweets, retweets, and favourites on topic in the OBSERVATION_PERIOD by its followers.

The concepts of Y_prop and reciprocity are shown in Figure 3. For instance, consider a user on Twitter, which is denoted as a central handle (CH) and has two followers, F_1 and F_2. A tweet (t_1) by CH on TOPIC is propagated to its followers, F_1 and F_2. If they retweet it or add it as their favourite, the tweet will reach the followers of F_1 and F_2. The total number of retweets and favourites of the tweet (t_1) by F_1 and F_2 and their followers provide the value of Y_prop. The reciprocity of the CH's network on TOPIC is obtained by tweets on TOPIC by the followers, F_1 and F_2, retweets, and favourites of the tweets on the TOPIC by Twitter users including CH.

For a CH, Y_prop and reciprocity are defined as (1) and (2)+(3), respectively.

Table 2 lists the variables measured for each central handle along with the mapping of each variable onto our theoretical framework, and Table 3 lists the descriptive statistics of the variables used in the model. Table 4 denotes correlation among the variables. The numbers shown in boldface denote significant correlation.

Figure 4 shows a portion of a Twitter handle timeline in which the tweet on blockchain is outlined. The unit of analysis in the regression model is the central handle that tweets on the TOPIC. CH tweets on TOPIC such as '# blockchain rapid develop blockchain solutions but avoid the complexities' among other tweets. Y_prop (=3) for CH is the number of retweets and

Table 2. Description of the variables.

Variable type	Variable name	Description	Construct	Possible values
Dependent Variable	Y_prop	Number of retweets and favourites of the tweets on a topic by the central handle		Any number from 0 to N (N is a finite number)
Independent Variables				
	Sentiment Valence	The ratio of the number of positive tweets to total tweets	Content	A number in the range [0, 1]
	Cval	The number of high-frequency topic related words used by CH	Content	Any number from 0 to N
	Focal.Ratio	Number of tweets on the topic divided by the number of tweets on Twitter	Content	A number in the range [0, 1]
	Engagement	Number of tweets, retweets and favourites on the TOPIC by CH	Content	Any number from 0 to N
	Structure	Number of followers of CH	Structure	Any number from 0 to N
	Reciprocity	Number of retweets, tweets and favourites on TOPIC by the network of CH	Reciprocity	Any number from 0 to N

Table 3. Descriptive statistics for the variables.

	Mean	St. Dev.	Min	Max
Y_prop	101.270	280.156	0	3173
Cval	102.199	328.310	0	3441
Structure	176.895	246.354	94	3634
Reciprocity	6462.85	11907.090	2	180,401
Focal Ratio	0.281	0.261	0.002	1
Engagement	146.375	267.827	1	2605
Sentiment Valence	0.378	0.226	0	0.973

favourites for all the tweets the CH wrote on TOPIC (=5). The Cval(=0.2829) is obtained by finding the similarity between the tweets CH made and keywords, as shown in the word cloud in Figure 1. Structure (=230) is the number of followers of the CH. Reciprocity (=372) is defined as the number of tweets, retweets, and favourites on TOPIC by its followers. Focal ratio is the ratio of the number of tweets he made on TOPIC(=5) out of 129 tweets in total. Engagement (=6) is defined as the number of tweets, retweets, and favourites made by CH on TOPIC over the time period.

4.3. Data modelling approach

In our work, we adopt a multi-method approach to test the hypotheses and research proposition proposed above. Multiple regression analysis (MRA) was used to ascertain the net effect of determinants based on the symmetric and linear relationship with the outcome

Table 4. Correlation Matrix.

	Y_prop	cval	structure	R	E	Focal_ratio	PR
Y_prop	**1.00**						
Cval	**0.17**	**1.00**					
Structure	0.04	0.07	**1.00**				
R	**0.48**	**0.31**	**0.15**	**1.00**			
E	**0.30**	**0.16**	**0.15**	**0.27**	**1.00**		
Focal_ratio	**0.36**	**0.39**	−0.01	**0.44**	0.02	**1.00**	
PR	0.07	**0.16**	0.04	**0.18**	**0.13**	**0.26**	**1.00**

Figure 4. Portion of a Twitter Handle's timeline.

variable. The variables identified to be significant in successful information propagation in MRA were further taken for fsQCA. In this way, fsQCA extends and supplements the MRA with a qualitative and case-oriented approach, where each unit of analysis is considered a case/configuration to ascertain how the different aspects of cases are interdependent (Ragin 2009). This multi-method approach also provides a methodological comparison of MRA, as we conducted fsQCA with the subset of the conditions listed in Table 2.

To test all the hypotheses (i.e. H1–H7), a multiple regression analysis was employed. Considering the independent variables (Cval, focal ratio, structure, reciprocity, and engagement) as influencing the propagation of the CH's tweets, we formulated the MRA model as follows:

$$\begin{aligned} ln(Y\_prop) = {} & \beta_0 + \beta_1 \ln(Sentiment\ Valence) \\ & + \beta_2 \ln(Cval) + \beta_3 \ln(Focal\ Ratio) \\ & + \beta_4 \ln(Structure) + \beta_5 \ln(Reciprocity) \\ & + \beta_6 \ln(Engagement) \\ & + \beta_7 \ln(Cval) * \ln(Reciprocity) \\ & + \beta_8 \ln(Focal\ Ratio) * \ln(Reciprocity) \\ & + \beta_9 \ln(Engagement) * \ln(Reciprocity) + \epsilon \end{aligned}$$

In this equation, β_0 is the intercept, and β_i (from 1 to 9) are the regression coefficients of the predictor variables or interaction terms. The predictor and moderator variables were mean-centered before generating the interaction terms to reduce multicollinearity. Furthermore, we inspected the variance inflation factors for the model. We found that the values ranged from 1.3–5.8, which were below the generally established threshold of 10 (Hair et al. 1998). This suggests that multicollinearity is unlikely to confound our findings. We used the log transformation of the variables to adjust for heteroscedasticity in the model.

In fsQCA, the relationship between multiple conditions is analysed with the idea of set memberships. Each case (unit of analysis) belongs to a configuration to some degree. In addition, degrees of membership vary across various configurations (Fiss 2011). The first step in fsQCA is the calibration of the variables in which they are converted into fuzzy sets, ranging from 0 to 1. A value of zero corresponds to null membership and one corresponds to full membership. The crossover point of 0.5 corresponds to maximal ambiguity (Fiss 2011; Woodside 2013). Using the direct calibration method, all the variables were calibrated using the 10th, 50th, and 90th percentiles corresponding to the three anchors for null membership, crossover, and full membership, respectively (Ragin 2009). The outcome variable is propagation strength, and causal conditions include the independent variables (i.e. content popularity, reciprocity, focal ratio, structure, and engagement), supported by the theory and proved significant in the regression model. To analyse sufficient conditions for information propagation, a truth table that lists all logically possible causal combinations of conditions is constructed. In our study, this amounts to 64 possible theoretical combinations resulting from five conditions emerging from five independent variables. Further, the truth table is reduced to meaningful and substantial configurations, based on the frequency and consistency levels. In this study, the frequency level, controlling the minimum number of cases supporting the configuration, was set to 5. The consistency level, which indicates the extent to which the configuration corresponds to the outcome, was set at 0.85. The configurations with consistency above 0.85, were considered sufficient for causing the outcome of interest (Leischnig and Kasper-Brauer 2015). The process was executed by the McKlusey algorithm using the QCA package in R (Dusa 2001).

5. Results

Table 5 lists the estimation results of the multiple regression model. The control variable included the sentiment valence of the central handle. Model 1 relates to the main effects of the variables CVAL, focal ratio, structure, engagement, and reciprocity on the propagation success on Twitter. Model 2 adds the moderating effects of reciprocity for propagating information and the variables content, focal ratio, and engagement. We also ascertained the impact of cval, focal ratio, structure, and engagement, barring reciprocity on information propagation strength. We found the adjusted R-squared value to be 0.683, which is higher than the value obtained in Model 1.

Table 5. Results of multiple linear regression.

	Model 1	Model 2
Sentiment Valence	−0.550	0.091
Cval	0.307***	0.307***
Focal Ratio	1.455***	1.371***
Structure	0.220	0.111
Reciprocity	0.383***	0.497***
Engagement	0.267***	0.261***
Cval*Reciprocity		−0.175***
Focal Ratio*Reciprocity		0.307
Engagement*Reciprocity		0.219***
N	371	371
R square	0.658	0.690
Adjusted R square	0.653	0.683
Residual standard error	1.135 (df = 364)	1.081 (df = 361)
F statistic	116.907*** (df = 6; 364)	102.241*** (df = 9; 361)

Note: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

H1 postulates that the network connectivity of the central node on Twitter has a positive impact on the propagation success of the Twitter handle. The results in Model 1 reveal that the coefficient of structure is positive but insignificant (β = 0.220, $p = 0.0147$). Therefore, Hypothesis 1 was not supported.

H 2.1 postulates that the popularity of content in a message has a positive effect on the propagation success of the Twitter handle. The results in Model 1 reveal that the coefficient of cval is positively significant (β = 0.307***, $p = 0.0000$). Therefore, Hypothesis 2.1 is supported.

H 2.2 postulates that the focal ratio of the central node has a positive impact on the propagation success of the Twitter handle. The results in Model 1 reveal that the coefficient of the focal ratio is positively significant (β = 1.455***, $p = 0.004$). Therefore, Hypothesis 2.2 is supported.

H 2.3 postulates that the engagement level of the central node on Twitter has a positive impact on the propagation success of the Twitter handle. The results in Model 1 reveal that the coefficient of engagement level is positively significant (β = 0.267***, $p = 0.00003$). Therefore, Hypothesis 2.3 is supported.

H3 postulates that the reciprocity of the network on the topic (as defined by retweets/tweets/favourites by the network on a particular topic) has a positive impact on the propagation success of the Twitter handle. The results in Model 1 reveal that the coefficient of reciprocity is positively significant (β = 0.383***, $p = 0.000$). Therefore, Hypothesis 3 is supported.

H4 postulates that the effect of the popularity of content in a message on the propagation success of the Twitter handle is accentuated in the presence of the network's reciprocity on the topic. The results in Model 2 reveal that the coefficient for the interaction between CVAL and reciprocity is statistically significant (β = −0.175***, $p = 0.0001$). Therefore, Hypothesis 4 is not supported. This interaction effect is plotted in Figure 5A to facilitate the interpretation of the results. The variable R_cat is defined to capture reciprocity at two levels (i.e. high reciprocity and low reciprocity). In Figure 5A, it is shown that CVAL positively affects the propagation success in the case of lower reciprocity of the central node's network, but this positive effect is suppressed in the case of higher reciprocity of the central node's network.

H5 postulates that the effect of the focal ratio on the propagation success of the Twitter handle is accentuated in the presence of the network's reciprocity wrt the topic. The results in Model 2 reveal that the coefficient of the coefficient for the interaction between focal ratio and reciprocity is positive but insignificant (β = 0.307, $p = 0.291$). Therefore, Hypothesis 5 was not supported. This interaction effect is plotted in Figure 5B to facilitate the interpretation of our results. The variable R_cat is defined to capture reciprocity at two levels: high reciprocity and low reciprocity. As shown in Figure 5B, the focal ratio has a positive impact on propagation success when the central node's network shows higher reciprocity, but this positive effect is weakened when the central node's network has lower reciprocity.

H6 postulates that the effect of engagement on the propagation success of the Twitter handle is accentuated in the presence of network reciprocity wrt the topic. The results in Model 2 reveal that the coefficient of interaction between engagement and reciprocity is positive and significant (β = 0.219***, $p = 0.0000$). Therefore, Hypothesis 6 was supported. This interaction effect is plotted in Figure 5C to facilitate the interpretation of our results. The variable R_cat is defined to capture reciprocity at two levels: high reciprocity and low reciprocity. As shown in Figure 5C, engagement has a positive impact on propagation success when the central

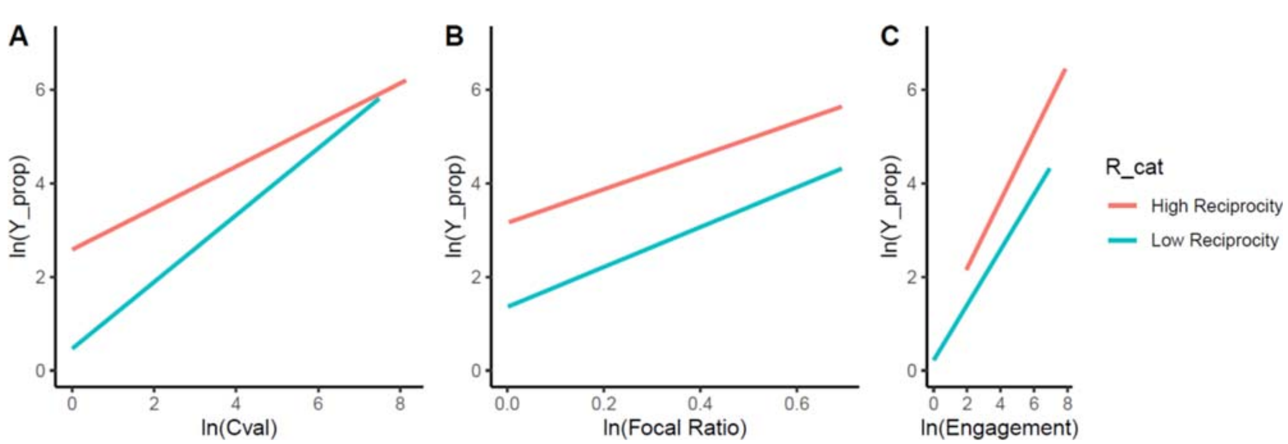


Figure 5. A, B, and C represent the interaction of Cval, focal ratio and engagement with reciprocity, respectively.

Table 6. Configurations identified from the fsQCA solution.

	Causal Configuration	Raw Coverage	Unique Coverage	Consistency	MRA Results
1	Cval*Reciprocity	0.668	0.016	0.877	Significant
2	Reciprocity*Engagement	0.692	0.026	0.871	Significant
3	Reciprocity*Focal.Ratio	0.685	0.030	0.858	Insignificant
4	Cval*Engagement*Focal.Ratio	0.625	0.053	0.910	Not tested
	Solution Coverage 0.825				
	Solution Consistency 0.807				

node's network shows higher reciprocity, but this positive effect is weakened when the central node's network has lower reciprocity.

The significant variables obtained from MRA (i.e. Cval, focal ratio, engagement, and reciprocity) are considered the possible conditions for successful propagation through configurational analysis, which generates three possible solutions, namely, complex, intermediate, and parsimonious (Fiss 2011). Table 6 lists the parsimonious solution, along with their consistency and coverage scores, which provide the required framework for analysing causal conditions. The last column of Table 6 denotes the corresponding MRA results. fsQCA evaluates the level to which a configuration accounts for an outcome through set-theoretic 'coverage' which is the sum of raw coverage and unique coverage. The raw coverage of a configuration refers to the portion of memberships in the outcome that is overlapped by certain configurations. This measure can be considered analogous to the R-square in regression analysis. The unique coverage indicates the proportion of memberships in the outcome, which is exclusively explained by one configuration (Tóth et al. 2015). The first configuration reveals content popularity and reciprocity, with a consistency level of 0.877, a raw coverage of 0.668, and a unique coverage of 0.016. The second configuration or recipe indicates the presence of reciprocity and engagement, showing a consistency level of 0.871, a raw coverage of 0.692, and a unique coverage of 0.026. The proposed model comprising all the configurations is determined as M1: Cval*Reciprocity+ Reciprocity*Engagement+ Reciprocity*Focal.Ratio+ Cval*Engagement*Focal.Ratio. In addition, the solution consistency and solution coverage are .807 and .825, respectively, which are acceptable values for both indicators (Woodside 2013).

The advantages of employing fsQCA analysis are twofold. First, it helps us validate the results obtained from the regression method. Second, it enriches our analysis by bringing about equifinality in the achievement of the outcome variable (Raab et al. 2013). The comparison of fsQCA results with MRA is given in Table 6. Configurations (1) and (2) are also manifested as a significant relationship between cval and engagement in the presence of reciprocity through MRA. Further, the interaction of focal ratio with reciprocity was insignificant in MRA but was revealed as a sufficient condition or configuration through a case-oriented approach adapted in fsQCA. The limitations of the net effects analyses explain the difference between the MRA and fsQCA results. Net effects analyses only examine the direct and indirect effects of individual independent variables on outcome variables and ignore the complexity of antecedent combinations in reality (Woodside 2013). Finally, the fourth configuration combining three variables (Cval, engagement, and focal ratio) shows the interdependence among these variables in influencing the outcome (Y_prop). Testing such higher-order interactions and their interpretation becomes challenging in multiple regression analyses (Woodside 2013). The overall solution of fsQCA, dented by four configurations, is a typical example of equifinality, as the four core conditions provide alternate paths to the successful propagation of information in the absence of one or more of the other conditions. The raw coverage of all three paths, i.e. 0.825, is relatively high, as they represent a substantial number of cases.

6. Discussion and implications

The current study contributes by providing a better explanation of a central node's influence, through the investigation of factors obtained from the perspective of the node itself (sender), as well as from that of the network (recipient). From the perspective of the sender/central node, it was found that factors such as content popularity, focal ratio, and engagement efforts strongly influence the user's propagation potential. First, as expected, content popularity was found to influence the user's propagation potential. This result reaffirms the importance of content popularity/user-interest similarity in enhancing the influence of the central node (Weng et al. 2010). Second,, the focal ratio also positively influences the information propagation potential of a user. This is similar to previous findings that emphasise users' topical focus in achieving a stronger influence (Alp and Öğüdücü 2018). Third, engagement efforts by users were also found to significantly impact their own overall propagation capability. This again corroborates the findings of earlier studies in which user influence was found to be highly correlated with user activity (Yu, Chen, and Ran 2016). Fourth, the role of network structure in influencing the user's overall propagation capability was found to be insignificant, which is not in agreement with previous findings (Goldenberg et al. 2009; Stephen and Toubia 2010). A possible reason for the same could be that a large number of followers may not necessarily guarantee a greater interest in the propagation of a specific topic. We believe that this finding merits further research.

From the perspective of the receiver (recipient network), the network's reciprocity towards the topic 'blockchain'was found to be significantly influencing the user's propagation potential. It is found that cooperators form network clusters when it comes to a particular topic (in this case, a technology in its nascent stage, blockchain), and help each other, utilising activities such as retweets, likes, and tweets that reflect the reciprocity characteristic. This corroborates with a few existing studies that adopt social exchange theory to understand information propagation behaviours and indicate that one of the key drivers of social exchange behaviours is reciprocity (Cheung, Liu, and Lee 2015). According to the reciprocity norm (Gouldner 1960), individuals in virtual communities can help each other directly or indirectly if support and learning are provided to the community in general. When users feel comfortable with the group, they often share content that other users can find relevant through a retweet, tweet, likes, etc. By forwarding a tweet along, the users not only amplify the topic-specific diffusion but also validate it. Retweeting can be a form of social advocacy where members become supporters of a user, brand (Malhotra, Malhotra, and See 2012), or topic. This is helpful to the central nodes because one primary motivation for them to post links on Twitter is the expectation of reciprocation from others in the network (Holton et al. 2014).

Further, the moderating influences of the network's reciprocity on the relationships between each of the three information propagation dimensions of the user (content popularity, focal ratio, and engagement) and his/her propagation potential is another contribution of this study. Looking at the results, first it was found that the reciprocal nature of the network on a particular topic reduces the impact of user's content popularity on his/her information propagation potential. A possible explanation could be that in the presence of a highly reciprocal network, rolling out content purely around high-frequency keywords in the network may appear routine and thus may not attract enough traction. This perception may lead to withdrawals, thereby reducing the information propagation potential of the user. A plausible strategy could be to strive to deliver unique, differentiated, creative content to ensure that others appreciate the topic from newer perspectives.

Examining the the moderating role of network reciprocity on the relationship between the user's focal ratio and his/her information propagation potential, our study reveals a positive, though, insignificant impact. A possible reason could be found in existing studies that have cautioned against assuming that the social media users, who are tweeting about 'blockchain' are experts. The literature suggests that information on Twitter is of low quality (Lee et al. 2016; Wang et al. 2013); thus, despite the high reciprocity of the network toward the topic of Blockchain, the propagation potential of the central node is not accentuated much, due to low quality content on the topic.

Finally, on examining the moderating role of network reciprocity on the relationship between the engagement efforts of a user and his/her information propagation potential, our study indicated a significant and positive impact. This is expected because in the presence of a highly reciprocal network, the user's engagement efforts would make a difference, as a highly enthusiastic network expects serious and continuous efforts from the central nodes and positively responds to such efforts, in turn enhancing the propagation strength of the node.

In summary, the findings of this study fill the gap identified in previous studies that call for newer studies to integrate novel network metrics such as reciprocity to generate useful insights in terms of information propagation in the social network of central nodes on various platforms (Arora et al. 2019). The findings could help information systems researchers and industries to adopt blockchain technology, dive into large-scale social media data, and discover useful data-driven insights that complement conventional technology diffusion research. This study also bridged the knowledge gap between current blockchain technology-related social media research and information propagation dimensions in social networks.

Further, the current study derived certain advantages by integrating fsQCA with multiple regression. As widely documented, the first advantage of configurational methods for studies with a moderately large sample size is the possibility of addressing multiple conjunctural causation in a straightforward manner. This is particularly important when it is likely, based on theory, that there are more ways than one to bring about the outcome or that the causal conditions combine in complex ways.

The fsQCA results obtained, broadly complement the regression model results in that they reaffirm the significant roles of content popularity, focal ratio, engagement efforts, and network reciprocity in the propagation of information about 'blockchain' on Twitter. Specifically, different configurations of network reciprocity toward the topic in conjunction with any of the propagation dimensions of content popularity, focal ratio, and engagement efforts by the central node are revealed to have the effect on the outcome (similar level of information propagation by the central node) or, in other words, equifinal configurations. In contrast with net effects analyses conducted by regression analysis that examined the direct and indirect effects of individual independent variables on outcome variable (i.e. information propagation by the central node), fsQCA identified combinations of causal conditions that can lead to the outcome of interest (i.e. information propagation by the central node). This technique maintains the integrity of individual cases in data analyses (Fiss 2011). In particular, fsQCA stresses that combinations of conditions result in an outcome rather than individual variables. Overall, the fsQCA results complement the results of the regression model in that they reaffirm the importance of network topical reciprocity in the propagation of information pertaining to 'blockchain technology' on Twitter. Further, combining the results and looking at the various configurations from fsQCA in conjunction with the regression (moderation) results, engagement efforts are found to significantly influence the information propagation potential of the node, in a situation of high reciprocity of the network towards the topic of blockchain, in both the results. The content popularity dimension was also found to significantly impact the propagation potential of the central node in the presence of high network reciprocity in fsQCA results, as observed in the regression results, although in the opposite direction. This finding, to our understanding, merits future research. Interestingly, the focal ratio whose impact on the propagation potential of the central node was identified to be insignificant in the presence of high network reciprocity in the regression results was found to be significant in influencing the information propagation potential of the node, in a situation of high reciprocity of the network toward the topic blockchain technology, in fsQCA results. A possible explanation could be that since regression results indicate net effects, individual net effects may nullify each other, suppressing the true interaction influence. The final significant configuration (including content popularity, focal ratio, engagement efforts, and network reciprocity) indicates the presence of higher-order interactions among the variables. However, this finding calls for future research. Interestingly, from different configurations that can produce superior propagation, it is noticeable that all the lower-order configurations are conditional on the network's reciprocity toward the topic of 'blockchain, reiterating its crucial role in the propagation success of a central node.

6.1. Practical contribution

This study is relevant for practitioners such as organisations and individuals (mostly in media, financial services, consulting, and IT) as they create campaigns in social media. Our study reveals the significance of a network that is reciprocal with respect to the topic, in propagating topic-specific information. It highlights the crucial role of active followers in the network, who are keen to further social capital with respect to a particular topic they feel or know to be newsworthy. Although understanding and building on popular content, topical focus, and engagement efforts by the central node remain prerequisites for information diffusion success of the node, on Twitter, the role played by the network's reciprocity in enhancing the user's influence cannot be undermined. Thus, listening to and observing the reciprocity of the network in relation to a particular topic and accordingly strategizing would enhance the central node's propagation potential. Additionally, the central node or user may intend to align one's content and activities/efforts with the level of reciprocity of the network for a topic with the objective of maximising influence. In general, empirical studies of information propagation networks generate practical insights into how to use social media as a medium to publicise information pertaining to a relatively new technology more efficiently. Further, with these collective insights, brand managers of social media platforms, who consider the segment of network users that reflect high reciprocity characteristics, can allocate resources to design and optimise diffusion strategies that heighten the impact of information propagation dimensions (especially the ones that are sufficient for strengthening the diffusion of the blockchain technology) and, thereby facilitate its legitimisation. To this end, knowledge about the specific configurations of propagation dimensions would be particularly helpful.

6.2. Limitations and future research

The limitation of our study is that the variable reciprocity accounts for the actions taken by the network and does not include users who are passive readers of the tweets. In addition, the generalizability of the findings beyond this context of nascent technology should be interpreted with some degree of caution. While the dataset utilised in the current study was large enough to draw conclusions confidently, a larger dataset is highly recommended for the generalisation of the conclusions to any future topic. Furthermore, future research may measure the impact of network reciprocity in the context of other social media platforms. Platforms with different capabilities can capture reciprocity in different ways. It would be interesting for future research to compare the reciprocity of users toward different kinds of topics, such as politics, sports, and tourism. In addition, longitudinal studies can be beneficial for tracing the diffusion of the topic 'blockchain' in various industries.

The present study also encourages future research concerning information propagation dimensions to move beyond the consideration of net-effects only or reliance on a single method and, instead, rely on multi-method approaches. A similar methodology can be used by future researchers to explore the diffusion of new technologies.

7. Conclusions

In summary, for a comprehensive understanding of how to engender successful propagation of information by a user, the literature appears to not convincingly account for the role of reciprocity of user's network. While research attests to the predictive quality of sender-specific variables such as content popularity, focal ratio, and engagement efforts of the central nodes for measuring their propagation potential, our study also takes cognisance of the role of network's reciprocity in strengthening the propagation potential of the central node. Thus, it additionally considers the variable of the network's reciprocity toward a particular topic (blockchain in this study) and its impact on the propagation potential of the central node. Further, the moderating role of the network's reciprocity on the relationships between the dimensions of content popularity, focal ratio, and engagement efforts of the user/central node and the user's/central node's propagation potential, is also mapped. The findings reveal that the network's users who are actively reciprocating on a particular topic (blockchain in this study), will be more approving of the central node's topic-specific initiatives/efforts and would exhibit much engaged/reciprocal behaviour in the process contributing to users' information propagation capability.

Blockchain was utilised as the topic for the current paper as it has the potential to disrupt multiple industries, especially those of IT and financial serviceHowever, at present, this digital innovation is in the early stages of diffusion, and its legitimacy has still not been established. Successful propagation of information related to blockchain technology may help related organisations demonstrate its legitimacy and ensure its wide acceptance. To achieve this, they may approach those users as nodes who meet the credentials of content popularity, focus/expertise, continuous engagement efforts and who can leverage the topical reciprocity of the network and maneuver their propagation strategies accordingly. Overall, we are able to clarify how the network's topical reciprocity is a crucial determinant of the overall influence of a particular user/central node in the context of a specific topic on Twitter.

In addition, this study has significantly advanced the understanding in the domain of information propagation by incorporating a multi-method approach, leveraging both quantitative and qualitative methods, and by demonstrating the need to consider the configurational effect of three propagation dimensions – content popularity, the focal ratio, user's/node's engagement initiatives, together with key network characteristic—reciprocity towards the topic, for successful information propagation in social media, rather than considering net effects only. The findings in this context further reveal that not all of the propagation dimensions necessarily matter equally and that different configurations of them can produce superior propagation, with all the lower-order configurations conditional on the network's reciprocity toward the topic of 'blockchain,' thereby reiterating its relevance.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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