SOCIAL MECHANISM OF SOCIAL SUPPORT PROVISION: A BEHAVIORAL STUDY OF ONLINE SUPPORT GROUPS

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ABSTRACT

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The popularity of Online Support Groups (OSGs) is ever increasing as OSGs enable people with (dis)similar health conditions to exchange social supports easily. Social support provision is a critical activity for individual well-being and community sustainability, yet the underlying social mechanism that promotes social support provision is underexplored. Employing social capital theory, the current study examines how brokerage and closure structures yield different forms of social capital such as non-redundant information and trust, which subsequently facilitate the diverse dimensions of informational and emotional support provisions, including quantity, quality, and timing. Methodologically, the study utilizes computational methods to collect online behavioral data from an online cancer community, measure network metrics and support provision behaviors, and capture the dynamic relationships between the network structure, social capital, and support provision behaviors. Results indicate that the brokerage structure and non-redundant information enhance the volume, uniqueness, and speed of information support provision. Although the closure structure and trust have a positive influence on the quality of emotional support, their overall impacts are limited in promoting information and emotional supports in the context of OSGs. The findings also indicate the importance of considering the dynamic development stage of OSGs in understanding the social mechanism of support provisions.

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INTRODUCTION

Online support groups (OSGs) provide virtual spheres where people with (dis)similar health conditions can connect and communicate with one another. By interacting with other members in OSGs, patients and informal caregivers (e.g., patients' friends or family) obtain useful information, practical advice, and emotional support that are less likely to be provided by medical professionals. As most OSGs are volunteer-based communities, members' continuous participation play an important role in the sustainability of OSGs. Among diverse activities performed in OSGs, social support provision is the most important activity for improving individual well-being and the sustainability of OSGs. Without support provision activities, the sustainability of OSGs is at risk, because receiving and exchanging social support is the major reason for people to visit and remain in an OSG (Ridings & Gefen, 2004). Despite the importance, the understanding of how *social support provisions* are promoted in the context of OSGs is lacking (Meng et al., 2017).

Social support provision is inherently social. Although support provision is an individual behavior, the source, motivation, and driving force of the behavior would be grounded in local and global social contexts where individuals exchange social support. Given that individual social context plays an important role in shaping, redirecting, and constraining social actions (Coleman, 1988), social support provision can be affected by the socially structured configuration in which individuals are embedded in. Although previous studies demonstrate the connection between social network structure and social support *reception* (Chen et al., 2021; Martí et al., 2017; Meng et al., 2016), the linkage between social network structure and social support *provision* is underexplored.

Employing a market metaphor, social capital theory provides a useful framework that explains how resources derived from a social network and relationships affect human behaviors. The current study uses social capital theory as a theoretical lens to understand how social structures built on social interactions and support exchanges in OSGs facilitate social support provision. Specifically, the current study focuses on *brokerage* and *closure* predominantly discussed in social capital theory to examine how these different types of network structures yield different forms of social capital (i.e., non-redundant information and trust), which subsequently play different roles in facilitating the provision of diverse social support.

Connecting social structure to social support behavior is a promising research area, yet not many studies have pursued this line of research trajectory (Meng et al., 2017) presumably due to methodological restrictions such as the high cost for collecting a large scale of social network data. Conceptual restrictions in defining and measuring diverse aspects of social and individual metrics from behavioral data also confine this type of study. Using the self-initiated nature of digital footprint and computational methods, the current study measures network metrics and social support behaviors in a more reliable and valid way. Given that a sound measurement reduces committing erroneous conclusions (e.g., Type I and II errors), network and behavioral metrics derived from digital traces help produce more robust results for the relationships between network and prosocial behaviors. Using digital footprint collected from a popular Korean OSG, the current study builds a large-scale support exchange network among members of the OSG and measure network, social capital, and support provisions to examine the social mechanism of social support provisions.

LITERATURE REVIEW

Social Support Provision: From Support Receiver to Support Provider

Scholars have conducted social support research since the 1970s. Over the decades, numerous studies have been conducted to understand the circumstances of maximizing social support effects (Cohen & Wills, 1985; Cutrona & Russell, 1990), various benefits of social supports (Guan et al., 2020; Han et al., 2019; Uchino et al., 2018), and the role of social network in the reception of social support (Chen et al., 2021; Martí et al., 2017; Meng et al., 2016). These studies found that social support is helpful to improve recipients' well-being (e.g., Hefner & Eisenberg, 2009), social support is more effective when the recipient is in high stress than low stress (e.g., Cohen & Wills, 1985), and the reception of different types of social support is partly determined by network position (e.g., Meng et al., 2016). Although these studies concern diverse aspects of social support, they mostly focus on social support from the perspective of *receivers* who demand social support. The other side, that is, *providers* who supply social support, is poorly understood.

Social support exchange is analogous to a market transaction. Given that a market transaction is better understood when we recognize the motivation and needs of both demand and supply sides, our understanding of social support exchange can be enhanced when we have a balanced understanding of both social support reception and provision. Among many questions related to support provision, the social mechanism that facilitates support provision behaviors is the focus of the current study. Specifically, the current study attempts to address the following questions: how does social context (or network) accrued from social interactions and support exchanges play a role in promoting social support provisions? What kind of social values and benefits (e.g., trust and diverse information environment) emerge through the networked relationship, and how do they affect social support provision in OSGs?

Although previous studies point out the importance of understanding social support provision in relation to social factors such as social norms (Maloney-Krichmar & Preece, 2005), shared identity (Wright & Bell, 2003), homophily (Wright, 2000), and reciprocity (Faraj & Johnson, 2011), findings are scattered presumably due to the absence of using a coherent theoretical framework that bridges social components and support provision (Meng et al., 2017). The caveat demands research that examines social support provision under the guidance of a theory that connects social components and support provision behaviors.

Conceptualizing Social Support Provision: Beyond Quantity

Social support provision refers to supportive actions and messages that an individual provides to others (Barrera, 1986). Social support provision differs from other social support concepts such as social embeddedness and perceived social support. Social embeddedness and perceived social support emphasize the potential social support resources (e.g., supportive connection or support availability) that an individual can rely on (Barrera, 1986), whereas social support provision emphasizes the behavioral aspect of social support. Although social support provision is conceptually identical to enacted social support that refers to supportive actions provided by others to a focal person (Barrera, 1986), this study intentionally uses the term "social support provision" instead of "enacted social support." Social support provision focuses on those who *provide* social support as the main subject, whereas the focal person in the definition of enacted social support is the one who receives social support. In that sense, enacted social support is often considered social support reception rather than social support provision in previous studies (e.g., Barrera et al., 1981; Kaul & Lakey, 2003). As support *provision* is the main target activity of the study, social support provision is more relevant terminology than enacted social support and therefore is consistently used throughout the study.

Unlike previous studies that solely focus on the quantity of social support provision (e.g., Huang et al., 2019), the current study will conceptualize social support provision as a multi-dimension concept that consists of quantity, quality, and timing. Given that quality and timing reflect behavioral aspects of supportiveness (e.g., providing valuable information; providing prompt help) that are different from the quantity (e.g., providing more support), integrating the quality and timing will capture a higher variance of social support provisions that are underexplored in previous studies. Moreover, as each of the concepts occupies a unique dimension of social support provision, examining each concept will provide a clear underlying mechanism that drives diverse aspects of social support provision. The study will conceptualize the quality of information support as the uniqueness of information given their supportive value in the context of OSGs. Moreover, the quality of emotional support will be conceptualized as the degree of reflecting a support seeker's expressions (Doré & Morris, 2018) as well as providing elaborated messages. Timing or speed of support provision will be conceptualized as the promptness of providing social support.

Social support literature has identified different types of social support. Cutrona and Suhr (1992)'s work is the most widely adopted topology of social support. They identified five different functions of social support: information, emotion, esteem, network, and tangible social supports. Among the five types of social support, the current study will focus on information and emotional supports as they are the most dominant types of social support in OSGs (Atwood et al., 2018; Braithwaite et al., 1999; Meier et al., 2007). Informational support concerns providing advice, factual information, and feedback to suggest coping strategies for the support seeker's actions or situations, whereas emotional support includes expressions of care, concern, empathy, and sympathy (Cutrona & Suhr, 1992). Although the ultimate goal of both informational and emotional social supports is the same for increasing individual well-being, they greatly differ in many aspects including the motivation and mechanism. Previous studies found that social relationships and tie strengths are associated with different types of social supports (Wellman & Wortley, 1990) and that mechanisms leading to informational and emotional support provision are different (Huang et al., 2019). Given the different nature of information and emotional support provisions, the theoretical paths leading to these different types of support behaviors must be examined. Hence, the current study will separate information and emotional support provision to expand pervious literature on the role of social mechanisms in the promotion of different types of social support.

In sum, the study will focus on two types of support provision (i.e., information support and emotional support) while considering three behavioral dimensions of each concept (i.e., quantity, quality, and timing). Given the different value nature of information and emotional support provision, the quality of information support provision will be represented by the uniqueness of information, and the degree of elaboration and reflection on recipients will represent the quality of emotional support provision.

Social Capital Theory: A Structural Perspective to Understand Social Support Provision

Previous studies examining antecedents of social support provision in OSGs show the importance of social and relational perspectives. Studies found that social norms influence online contributions (e.g., Maloney-Krichmar & Preece, 2005). Other studies revealed that the characteristics of OSGs such as high homophily and high attachment encourage social support provisions (Kordzadeh et al., 2014; McLeod et al., 2020; Wright, 2000). A study also argues that strong emotional bonds built upon shared identity and empathetic communication promote social support provisions in OSGs (Wright & Bell, 2003). Although not examined in the context of OSGs, findings from information system research indicate that weak ties facilitate information support provision as people with weak ties have access to a wide range of information (e.g., Levin & Cross, 2004). The above evidence suggests that considering the social context in OSGs will provide insights to understand the restriction and promotion of social support provision.

Social capital theory is a useful framework to understand the role of social context in mobilizing social actions (Coleman, 1988). Social capital refers to "the resource available to actors as a function of their location in the structure of their social relations" (Adler & Kwon, 2002, p. 18). As a form of capital, social capital facilitates productive activity as much as physical (e.g., money) and human capital (e.g., human skills) do (Coleman, 1988). However, unlike other forms of capital, social capital is inherently embedded in the structure of relations between actors and among actors (Coleman, 1988). As a resource derived from social connections, social capital enables connected individuals to take advantage of benefits such as increased accessibility to non-redundant information (Burt, 2007), enhancement of social belongings (Burt, 2007), and fostering social actions (Coleman, 1988) including knowledge transferring (Walter et al., 2007) and social support exchanges (Wellman & Wortley, 1990).

Social capital theory argues that some people do better because they are better connected with others (Burt, 2007). Brokerage (Coleman, 1988) and closure (Burt, 1992) are the two types of network structure that represent "better connection" in social capital literature. Although both brokerage and closure contribute to generating social capital, each of the structures is more suitable than the other to yield different forms of social capital (Coleman, 1988), which may subsequently affect social support provision. Experiencing non-redundant information is a form of social capital promoted in the brokerage structure, whereas trust is a form of social capital that is likely to emerge in the closed network structure (Coleman, 1988). As brokerage and closure yield different forms of social capital, they may have different impacts and implications for different types of social support provision.

Characteristics of Brokerage and Its Relationship with Social Support Provision

Brokerage is conceptually defined as the network structure in which individuals span across groups (Burt, 2007). Actors embedded in the brokerage position in a network are called brokers, and brokers benefit themselves by spanning across structural holes that exist between groups that are weakly connected. As brokers have weak but diversified and non-redundant connections that invite people from various backgrounds, they are privileged to access diverse information that overlaps less with each other (i.e., non-redundant information) (Burt, 1992, 2007). Access to non-redundant information provides brokers with an opportunity to expand their knowledge and develop novel ideas (Kwon et al., 2020). A number of studies have documented that brokers demonstrate high creativity (Li et al., 2018), generate good ideas (Burt, 2004), and deliver unique information (Aral & Dhillon, 2022).

In the context of social support, it is predicted that brokerage facilitates information support provision, but not necessarily emotional support. Brokerage is featured with diversified but weak connections. On the one hand, diversified connections in a brokerage are advantageous to increase one's ability to provide information support with increased and diversified knowledge. While being exposed to non-redundant information, brokers will develop knowledge on diverse topics and increase their capability and confidence in providing informational social support. Given that such confidence (also known as self-efficacy) is a key component that facilitates behaviors (Bandura et al., 1999), brokers will provide more informational social support with increased capacity derived from the bridging structure. On the other hand, given the reliance on shallow relationships, a brokerage does not facilitate offering emotional supports (Shen & Cage, 2015), which are typically given to those who are based on strong relationships (Walker et al., 1993). Moreover, given that similarity plays an important role in increasing empathy which is a strong motivation for emotional support (Burleson, 1983; Rains & Wright, 2016), the prevalence of dissimilarity among a group of people in a brokerage will discourage emotional support provision.

Beyond the quantity, brokers will provide more valuable information that contains unique information in a timely manner compared to non-brokers. Provision of unique information is critical in the context of OSGs because it helps members who explore possible options make an informed decision. Empirical evidence suggests that brokers featured with weak bridging ties contribute to delivering the most unique information (Aral & Dhillon, 2022). In addition to information uniqueness, brokers will be able to provide faster information aid than non-brokers as they are privileged to access information early (Burt, 2007). The early accessibility to information will help brokers keep up-to-date which may enable them to provide information support more promptly than non-brokers those who are less up-to-date.

H1a-c: Brokerage positions occupied by an individual user in an OSG will lead to a) high volume, b) unique, and c) fast speed of information support provision.

Non-redundant Information as Social Capital Mediating Brokerage and Social Support Provision

The current study views brokerage as a structural source of social capital rather than social capital itself. Social capital is defined as resources or advantages available to actors due to their position in a network (Adler & Kwon, 2002; Burt, 2007). Hence, a non-redundant information environment can be considered a form of social capital derived from a brokerage structure (non-redundant information is described as an advantage in Burt, 2007; and as an outcome in Kwon et al., 2020). As discussed earlier, a brokerage structure consists of weak ties that connect individuals from diverse backgrounds (Burt, 2007). In a diverse environment, brokers are likely to be exposed to and experience information that overlaps less with one another. Although empirical evidence is lacking, previous studies have documented the knowledge benefits of non-redundant information such as generating more good ideas and increasing creativity (see Kwon et al., 2020).

In the context of OSGs, the non-redundant information environment would be the reason why brokerage facilitates diverse dimensions of information support provisions. By experiencing non-redundant information, brokers will develop knowledge on diverse topics (Burt, 2007), which will increase their capacity for providing more information support. Moreover, brokers will be able to provide unique information because brokers have more opportunities to generate unique and new ideas by combining non-redundant information (Li et al., 2018). As they spend less time finding or generating this unique and valuable information by being in a non-redundant information environment (Fleming et al., 2007), they will be able to provide information support promptly. That is, a positive linkage will exist from brokerage to non-redundant information and from non-redundant information to the diverse aspects of information support provisions, which suggests a mediating role of non-redundant information.

H2a-c: Non-redundant information will mediate the relationship between brokerage and a) the volume, b) uniqueness, and c) speed of information support provision.

Characteristics of Closure and Its Relationship with Social Support Provision

Closure is a network structure in which individuals are densely connected with one another (Burt, 2001). Closure is featured with strong ties and closed structure wherein trust is likely to emerge among members (Coleman, 1988). Prosocial behaviors will be promoted and obligated in a closed network as individuals have a trustful belief that their behaviors for others will be repaid (Coleman, 1988). As members in closed social structures are densely and directly connected, closure facilitates communication among members. With frequent and direct communication, members will develop shared values, mutual awareness of needs, and mobility of social help (Wellman & Frank, 2017).

In the context of social support, members embedded in closure will be more likely to provide both informational and emotional social support than members in less closed structures. In general, closure consists of strong ties that provide great motivation for assistance (Granovetter, 1983). People connected through strong ties exchange a broader range of social supports including companionship, minor services, and emotional support (Wellman & Wortley, 1990). Although strong ties are disadvantageous to deliver unique information (Aral & Dhillon, 2022), members will still make efforts to provide information support as they do not want other members suffer from a lack of information. Empirical evidence substantiates that network features related to closure, such as strong ties and cohesion, facilitate knowledge transfers and exchanges (Tortoriello et al., 2012). Furthermore, closure will promote emotional support through the development of a trustful relationship (Heaney & Israel, 2008). Under a trustful environment, members feel safe to express their deep feelings and concerns (Wheeless & Grotz, 1977). Given that such emotional self-disclosure facilitates emotional support exchanges (Pan et al., 2018), members in closure will be more likely not only to receive emotional social supports

(Chen et al., 2021; Meng et al., 2016) but also provide them to others. Therefore, the current study predicts positive associations between closure and the amount of information and emotional support.

H3a-b: Closure positions occupied by an individual user in an OSG will lead to high volume of a) information support provision and b) emotional support provision.

Trust as Social Capital Mediating Closure and Social Support Provision

Like brokerage, closure is a source of social capital. Trust is the form of social capital that can be derived from closed networks (Coleman, 1988). While maintaining intimate relationships with other members in a closed network, people develop trust toward other members. Notably, trust developed in a local network is generalizable to the whole online community (Pavlou & Gefen, 2004). A previous study found that people decide whether others are generally trustworthy or not on the basis of local interactions (Glanville & Paxton, 2007). Thus, one's trust in members of a local network is generalized to trust other general members of an OSG. As trust is more facilitated in a closed network than in other forms of a network, generalized trust will be higher for members of a closed network. In the current study, trust refers to one's trust in an online support community (Pavlou & Gefen, 2004). Specifically, trust is defined as a trusting behavior that exhibits one's willingness to be vulnerable to members of an OSG (Zand, 1972). In the context of OSGs, self-disclosure can signal a trusting behavior as self-disclosure represents one's willingness to be vulnerable to others by revealing personal and sensitive information (Huang et al., 2019). By trusting that other members will not abuse what they disclose, one will be willing to disclose their sensitive experiences that they would not share with distrusted others (Huang et al., 2019).

Trust is an important social component that facilitates social interactions including monetary transactions in e-commerce (Harrison McKnight et al., 2002) and knowledge sharing in online communities (Ridings & Gefen, 2004). In the contexts of OSGs, trust will facilitate informational and emotional social support. In a trustful relationship, individuals are supportive as they become increasingly concerned about others' welfare and needs (McAllister, 1995). Members in a closed network will provide informational and emotional social support as they trust that other members will provide social support for them when they need it. Therefore, the study expects that trust derived from closure will mediate the relationship between closure and the quantity of information and emotional support.

H4a-b: Trust will mediate the relationship between closure and the volume of a) information support provision and b) emotional support provision.

Quality is different from quantity. Even though closure facilitates the provision of information and emotional support through enhanced trust, people in closure do not necessarily provide valuable information support containing unique information in a timely manner. Redundant information is circulated in a closed network (Burt, 2001). Such redundancy may prevent members from providing unique information and slow down the pace of information support provision as members may need more time to find useful information for other members. On the contrary, closure will facilitate higher quality and more rapid emotional support provisions through enhanced trust. As noted earlier, trust derived from closure can make one feel safe to share their emotional stories (Wheeless & Grotz, 1977). Through the exchange of affective self-disclosure, members will have higher emotional understanding of one another and strengthen their trustful relationship, which will help them provide a higher quality of emotional support. Moreover, as trust encourages members to care about others' welfare and needs

(McAllister, 1995), it will facilitate members to provide emotional support promptly when they are solicited. Figure 1 illustrates the proposed research model.

H5a-b: Closure positions occupied by an individual user in an OSG will lead to a) high quality and b) fast speed of emotional support provision.

H6a-b: Trust will mediate the relationship between closure and a) the quality and b) speed of emotional support provision.

A great level of social dynamics is present in OSGs, as many people join and leave OSGs. In general, a successful OSG steadily grows as the number of incoming new members surpasses the number of members who drop out. This social dynamic of OSGs may impact the way network and social capital plays a role in affecting social support provisions. In the early development phase of an OSG where only a few members join and interact with one another, members may have more chances to get to know one another and develop close relationships. While members develop dense and strong connections with one another, structural holes would be filled, and redundant information may overflow in the early stage of an OSG. In such a circumstance where community size is small, closure structures and trust among members will be facilitated (Allcott et al., 2007), whereas brokerage structures and non-redundant information may be less promoted. In the later stage of an OSG where community size expands with incoming new members, the dynamics between network structures and social capital may evolve and their roles in promoting social support provisions may change as well. Based on the speculation, the study proposes a research question that examines whether the relationships among network structures, social capital, and social support provisions change accordingly with the development stage of OSGs (i.e., early, growth, and mature stages).

RQ1: Will the development stage of OSGs moderate the relationships among network structures, social capital, and social support provision?

METHODS

Data Collection, Cleaning, and Sampling

Data were collected from one of the popular online cancer communities in South Korea. With exemption, Institutional Review Board (IRB) approved data collection. Python was used to crawl 12 years' worth of data from the online cancer community, and data collection took 12 days. After data collection was completed, each user ID was replaced with a six-digit random number to mask the identity of individual members. The collected data include user's ID, user-generated posts and comments[1], categories of posts, the number of views on posts, and a timestamp of content which ranges from August 13, 2007, to November 25, 2019. In total, 208,261 posts and 1,998,135 replies were collected. Unwanted artifacts such as empty content, misaligned data, and duplications that occurred during the data collection process due to technical glitches were handled. Specifically, posts and comments that include empty or misaligned data were removed. In the case of duplications, only unique data were retained. The number of posts and replies were reduced to 204,720 and 1,954,209, respectively, after data cleaning. A total of 54,207 unique users updated at least either a post or a comment in the OSG.

Figure 2 illustrates the research design. The study removed the data from the first two years (i.e., 2007 and 2008) and the last year (i.e., 2019) due to the instability of community and incompleteness of data, respectively. The remaining data from 2009 to 2018 were used for analysis. The study generated 20 panel data (i.e., two panels per year), each of which consists of four months. Given that many users in online communities do not stay in one community for an

[1] A post is content that initiates discussion. A comment is a user's response to a post.

extended time, the period of four months is an appropriate time frame that allows the study to collect enough user behavioral data before facing a high dropout rate. For each year, spring and fall panel data were generated. Each of the spring panel datasets ranges from January to April, and each of the fall panel datasets ranges from September to December. The first batch of panel data (i.e., January to March in spring panel or September to November in fall panel) served to construct network structure (i.e., independent variables) and social capital metrics (i.e., mediators). The second batch of panel data (i.e., April in spring panel or December in fall panel) were used to measure social support provision (i.e., dependent variables). The research design strengthens a causality examination by incorporating time dimension and controlling for potential confounders derived from year and seasonal impacts.

A valid sample is chosen on the basis of user activities and interactions with other users. For each user, some degrees of activities and interactions are required to measure their network structures, social capital, and support provisions. In the current study, two criteria are used to select a valid study sample. First, a user must interact with at least two other members in the first batch of panel data used to measure network structure and social capital. Second, the same user should provide at least both one information and one emotional social support in the second batch of panel data used to measure support provision. When an individual appears in multiple panel datasets (e.g., individuals who appear in January–April 2010 and September–December 2010), the researcher treats the individual independently across different panel datasets instead of dropping the individual from the study. This approach helps the study retain more data and simplifies the study analysis. To account for the dynamic nature of the OSG, panel datasets were grouped into the early stage (2009–2012), growth stage (2013–2016), and mature stage (2017–2018) on the basis of the OSG's growth rate. The unit of analysis is an individual who provides social support. The number of valid sample sizes are 343 in the early stage, 2,178 in the growth stage, and 2,765 in the mature stage.

Measurements

Social Support Provision

In the current study, social support provision is operationalized as a message written to help others informationally, emotionally, or in other ways. Among these social support provisions, information support provision is a message that provides guidance or advice on resolving problems, and emotional support provision is a message that comforts the other person's feelings through empathy, sympathy, or caring (Cutrona & Russell, 1990).

A supervised machine learning was utilized to classify informational and emotional social support provisions. Five coders were hired to generate train and test datasets for machine learning. Coders evaluated the intended behavior of content, focusing on whether the content is social support provision, social support seeking, or others. If content was classified as social support provision, then coders further evaluated the support type, focusing on whether the content is informational or emotional, or other types of support (Cutrona & Russell, 1990). Krippendorff's alpha reliability was used to check intercoder reliability (Krippendorff, 2018). A substantial level of intercoder reliability was reached over the training phase ($\alpha_{\text{intended behavior}} = .78$; $\alpha_{\text{support type}} = .72$) and the main task phase ($\alpha_{\text{intended behavior}} = .78$; $\alpha_{\text{support type}} = .71$). Coders generated 7,654 label data. The labelled data were split into a training dataset (n = 6,123) and testing dataset (n = 1,531) for machine learning-based classification.

BERT, which is a cutting-edge natural language processing model originally developed by Google, was employed to classify intended behaviors (i.e., support provision; support seeking; others) and support types (i.e., information support; emotional support; others) automatically (Devlin et al., 2019). Specifically, the study adopted aa Korean version of BERT (KoBERT) developed by a group of Korean researchers (SKT Brain, 2022). The pre-trained KoBERT was finetuned with the training dataset while parameters were set to 20 epochs and a batch size of 65. The performance of the finetuned KoBERT was evaluated using the testing dataset on the basis of the accuracy score, which refers to the proportion of correctly classified cases. The finetuned KoBERT's accuracy score was 78% for intended behavior and 77% for support type. A message was identified as an information support provision if it is classified as support provision in the intended behavior and information support in the support type. A message was identified as an emotional support provision if it is classified as support provision in the intended behavior and emotional support in the support type.

Support provision can be made either through a post (i.e., initiating discussion) or a comment that responds to a post. Support provision made through a post targets an unspecified mass audience (e.g., providing information to general audiences), whereas support provision made through a comment targets a specific individual who seeks social support. The study considers only the latter form which is the most common type of support provision in the study. The machine learning result shows that 97% of support provision is made through comments. Furthermore, in cases wherein a support provider provides multiple information and emotional support provisions in a thread, the study considers only the first information and emotional support provision for the sake of analytic simplicity.

Volume The volume of informational support provision was measured by counting the number of information supports that a user provides during the study period. In the same way, the volume of emotional social support provision was measured as the number of emotional supports that a user provides during the study period. To alleviate skewness of data, the volumes of information and emotional support provisions were log transformed.

Speed The speed of information support provision was measured by computing the time difference between the information support request and the information support provision. For each user, the averaged time difference across threads that a target user participates in was used to indicate the response time of the target user. To alleviate skewness of data, the response time of information support provision was log transformed. Then, the log-transformed response time is reverse-coded by subtracting it from the maximum value. Reverse coding was executed to make the value interpretation consistent with other dependent variables (i.e., the larger value, the better). The speed of emotional support provision was measured in the same way.

Uniqueness of Information Support Information uniqueness is conceptualized as information that is distinct from existing information (Aral & Dhillon, 2022). Information uniqueness between two texts can be quantified by evaluating how much the two texts are semantically independent. To measure information uniqueness, first, a semantic vector of each text was estimated through a Korean-sentence BERT-embedding model which was developed on the basis of KoBERT (jhgan00 [github user ID], 2021). Text embedding is a text mining technique that converts text to a numeric vector so that diverse text analyses including a semantic comparison can be performed. BERT embedding is chosen as it has shown better performance for document embedding than other embedding models (e.g., TF–IDF embedding and doc2vec) (Ajallouda et al., 2022). After estimating the vector for each text, a cosine similarity algorithm was used to measure the semantic similarity between information that a focal person provides and information that another person provides in a thread. Cosine similarity ranges from −1, meaning semantically opposite, to 1, meaning semantically same. Values close to 0 indicate that two semantic vectors are independent, which may indicate that a target information is semantically more unique from another information. As values close to 0 capture the uniqueness of information rather than positive or negative values, the absolute value of a cosine similarity score will be used in the study. To make the value intuitive and relevant to information uniqueness, 1 will be subtracted by the absolute value of cosine similarity; thus, a higher value will indicate higher uniqueness of target information compared to another information as two texts are semantically different. For each thread wherein a focal person provides information support, the focal person's information support is compared with each of information supports provided by others and then averaged. Information uniqueness of an individual i is measured by using the following formula:

$$\text{Information uniqueness}_i = \frac{\sum \frac{(1 - |\cos(IV_{in}, IV_{jn})|)}{n_p}}{n},$$

where IV_{in} is a semantic vector of focal person i's information support provision to the nth post that requests support; IV_{jn} is a semantic vector of information support provided by another person other than focal person i to the nth post; n_p is the number of pairs of focal person's information support provisions that are compared with others' support information support provisions; n is the number of posts in which focal person i provides information support for. A missing value is produced when no one, but only i provides information support (n = 489) in a thread. In that case, a missing value is replaced with the mean value of information uniqueness. Thus, information uniqueness of focal person i is estimated by dividing the sum of averaged information uniqueness at the thread level by the number of threads in which the focal person provides information support for.

Quality of Emotional Support Quality of emotional support provision is conceptualized as both the degree of reflection on a support seeker and elaboration of emotional support provision on the basis of the argument in person-centered message literature. Person-centered message is an established framework that outlines different levels of emotional support quality. According to the framework, a high quality of emotional support explicitly acknowledges and provides an elaborated explanation of a support seeker's feelings (High & Dillard, 2012). To acknowledge and reflect a seeker's feelings, an individual who provides a high quality of emotional support will accommodate their language to the support seeker's language. Such adjustment will make the support provision message semantically similar to the support-seeking post. Based on this notion, a previous study used text similarity as an indicator of emotional support quality (Doré & Morris, 2018). To elaborate the recipient's feelings, a high quality emotional message will be generally lengthier than a lower quality message. According to the theoretical conceptualization, in the current study, quality of emotional support was computationally measured using a composite score where text similarity between emotional support provision content and support seeking content (i.e., the degree of reflection) is weighted by the length of emotional support provision content (i.e., the degree of elaboration). The Korean-sentence BERT-embedding model, which is used for measuring information uniqueness, was used to estimate semantic vectors of emotional support provision contents. The following formula was used to represent quality of emotional support of a focal person:

$$\text{Quality of emotional support}_i = \cos(EV_{in}, EV_n) * length_{in},$$

where EV_{in} is a semantic vector of i's emotional support provision to the nth post that requests emotional support; EV_n is a semantic vector of the nth post; $length_{in}$ is a log-transformed and normalized length of i's emotional support provision to the nth post. To compute $length_{in}$, the length of i's emotional support provision to the nth post was log-transformed and then normalized through the min-max normalization technique to match its scale with that of cosine similarity. The min-max normalization technique essentially makes the minimum score 0, which is problematic as it will make a composite score 0 when multiplying cosine similarity score and length. To handle the issue, a trivial constant score of .01 was added to a normalized score.

Network Structure

Each panel's social support exchange network derived from posting and commenting activities is used to measure a focal person's brokerage and closure.

Brokerage Brokerage is a structural position in which an individual plays a role in bridging pairs of disconnected others (Burt, 1992). Several measurements including betweenness centrality (Freeman, 1977), network constraint (Burt, 1980), and effective size (Burt, 1992) have been introduced to measure brokerage. The current study used betweenness centrality to measure brokerage because betweenness centrality allows the researcher to account for edge weight, which carries rich information about bridging in the measurement (Opsahl et al., 2010). Betweenness centrality measures the extent to which a focal person lies on the shortest paths between other actors (Freeman, 1977). Although the shortest path is determined by minimizing the number of intermediary nodes in a binary network, Opsahl et al.'s (2010) approach, which is used in the study, measures the shortest path in a weighted network by taking both the number of intermediary nodes and edge weights into account. An R-package called bipartite was used to measure betweenness centrality in a weighted network (Dormann et al., 2014). Betweenness centrality was log-transformed to reduce the skewness of data.

Closure Closure is a structural position in which an individual links others that have existing connections (Burt, 1992). Closure occurs when a tie is added to close a 2-length path to form a triangle, which is known as triadic closure (Opsahl, 2013). A weighted local clustering coefficient was used to measure closure. As opposed to the unweighted local clustering coefficient that simply counts the proportion of triadic closure, a weighted local clustering coefficient measures the same concept while taking edge weights explicitly into account (Saramäki et al., 2007). As edge weights carry more information about relationships of members (e.g., frequency of social support exchanges), the weighted local clustering coefficient would better reflect the nuanced relational properties of a network system than the unweighted local clustering coefficient (Saramäki et al., 2007). Studies have proposed different weighted local clustering coefficients (Saramäki et al., 2007) through different normalization methods (e.g., arithmetic mean, geometric mean, maximum, or minimum of the two tie weights). The study used Onnela et al.'s (2005) method, which normalizes the edge weights on the basis of the maximum weight in the network (i.e., the geometric mean of edge weight method). An R-package called DirectedClustering was used to measure the closure structure of each node by using Onnela's method. Closure is log-transformed to reduce the skewness of data.

Social Capital

Non-redundant Information Non-redundant information refers to non-overlapping information that a focal person experienced. A focal person would experience non-redundant information when information that they experience differs across each other. Thus, the degree of information difference among content that a focal person experiences can be used to indicate the focal person's non-redundant information environment. To measure non-redundant information, first, a focal person's information environment was compiled by collecting others' messages that a focal person experienced. Without log data, knowing what messages a focal person experienced is infeasible. To address the issue, the study made assumptions. When a focal person updated a post, the current study assumes that the focal person would read all comments because all comments are addressed to the focal person. When a focal person made a comment to a post written by another person, the focal person is assumed to have read the post and comments made prior to the focal person's comment. After compiling messages that a focal person experienced, each message's vector estimated by using Korean-sentence BERT was compared with one another, and the semantic differences across messages were averaged to indicate non-redundant information of a focal person. The author sets a threshold for the number of paired content as it is computationally too expansive to compare paired contents when a focal person has a large scale of information environment. If the number of paired contents is more than or equal to 1,000, only 1,000 pairs were randomly selected. Mathematically, the following formula was used:

$$\text{Non-redundant information}_i = \frac{\sum(1-|\cos(M_j, M_q)|)}{n},$$

where M_j and M_q are vectors of message j and message q, respectively. These messages were posted by others, and n is the number of paired messages. That is, the function in the numerator computes information differences across messages that a focal person i experienced and the sum of information difference is divided by the number of paired messages to indicate non-redundant information of focal person i.

Trust In the study, trust is conceptualized as trusting behavior representing one's willingness to be vulnerable in an OSG (Zand, 1972). Given that trust in others developed through local interactions (e.g., interactions in a closed network) is generalized to others in a community (Glanville & Paxton, 2007; Stewart, 2003), trust in an OSG is measured instead of measuring trust in a specific group of people. In the context of social support exchanges, one can be vulnerable by disclosing his/her personal and sensitive experiences to others. Therefore, trust is operationalized as the degree of self-disclosure in messages that a focal person shares in an OSG (Huang et al., 2019). A previous study measure trust with the degree of self-disclosure by counting the proportion of words related to self-disclosure including first-person singular pronouns (e.g., I, my), first-person plural pronouns (e.g., we, our), family (e.g., husband, mom), friends (e.g., neighbor, girlfriend), positive emotions (e.g., love), and negative emotions (e.g., sad, hurt) (Huang et al., 2019). A dictionary containing Korean words related to self-disclosure was constructed on the basis of the researcher's domain knowledge and by referring to online materials (*Korean Family Terms*, 2022; On et al., 2018). On the basis of the constructed dictionary, trust was measured by counting the proportion of self-disclosure words in messages that a focal person updated.

$$\text{Trust}_i = \frac{\text{Total number of self−disclosure words}_i}{\text{Total number of words}_i}$$

Control Variables

Individual post activity (i.e., initiating discussion) was controlled. Post activity is measured by counting the number of posts that a focal person uploaded during the four months of the study period. To reduce skewness, the control variable was log-transformed. Table 2 provides an overview of the study variables and their operationalizations.

Analytic Plans

To test the research hypotheses and the research question, two multigroup path analyses were conducted using an R-package called lavaan (Rosseel et al., 2017). First, the coefficient-constrained multigroup model was constructed to examine the research hypotheses. The coefficient-constrained multigroup model, which assumes that loadings (or coefficients) are identical among groups (i.e., early, growth, and mature stages) allows the researcher to estimate the overall associations among variables regardless of the group factor.

To examine the proposed research question, a coefficient-free multigroup model was constructed and compared with a coefficient-constrained multigroup model. Compared to a coefficient-constrained model that sets fixed loadings across groups, a coefficient-free multigroup model allows groups to have varying coefficients. By comparing a coefficient-free model and a coefficient-constrained model through the chi-square difference test, one can examine whether the effects of structural path statistically differ across various groups. Thus, the comparison between the two models allows for examining whether the paths are moderated by the group factor.

RESULTS

Descriptive Results

The total sample size of the data is 5,286. The sample consists of 3,623 unique users, 73% (n = 2,649) of which appear once in a panel dataset and 27% (n = 974) of which appear more than once across panel datasets. On average, the target individuals updated 5 posts (*SD* = 8.50, median = 3) and 47 comments (*SD* = 107.99, median = 17) during the four months of the study period. Among uploaded content, 51% of them is support provision, 12% is support seeking, 37% is others (e.g., gratitude expression). Among support-provision content, 48% is information support and 36% is emotional support, which indicates that information and emotional support provision (84%) are the dominant types of social support compared to other types of social support (16%).

Descriptive network statistics of the OSG at different development stages helps understand the study context. The data for the following descriptive statistics based on activities from not only the target users but also other members who were active and potentially interacted with target members during the study period. Figure 3 provides examples of community-level network at the early, growth, and mature stages. As shown in Figure 3, the community network increased over time. The average network size in the early stage is about 581, and it increased to 4,283 in the growth stage and to 6,942 in the mature stage. As the community grew, a member's personal network also expanded. The degree centrality metrics indicate that a member interacted with 7 other members on average in the early stage, and the number expanded to 11 in the growth stage and to 12 in the mature stage. The index for brokerage structure also increased over time. While the community grew, the density representing the overall connections among members decreased over time. Moreover, the degree of individuals' closure structure decreased.

Table 3 summarizes the detailed descriptive statistics of the OSG community across the study panels.

Hypotheses Testing

The model fit indices indicate that the proposed research model is acceptable ($\chi^2(87) = 606.03$, $p < .001$, CFI = .92, RMSEA = .06, SRMR = .04). The model largely supports hypotheses related to paths from brokerage, non-redundancy, to information support provisions. However, only a few hypotheses concerning closure and trust are supported. Table 4 provides the summary of the results.

H1a, H1b, and H1c concern the direct effect of brokerage on information support provision. Consistent with H1a and H1b, individuals provide more information support ($\beta = .13$, $p < .001$) and a higher level of unique information ($\beta = .04$, $p < .05$) when they are embedded in a higher level of brokerage position. However, brokerage does not facilitate the speed of information support provision ($\beta = .02$, $p = .24$). Therefore, H1a and H1b are supported, whereas H1c is rejected.

H2a, H2b, and H2c concern the mediating role of non-redundant information. Consistent with the hypotheses, non-redundant information mediates the relationships between brokerage and information support volume ($\beta = .05$, $p < .001$), brokerage and information support uniqueness ($\beta = .03$, $p < .001$), and brokerage and information support speed ($\beta = .01$, $p < .001$). Therefore, H2a, H2b, and H2c are supported.

H3a and H3b predict the positive direct effect of closure on information support volume and emotional support volume, respectively. Inconsistent with the predictions, closure has a negative effect on information support volume ($\beta = -.05$, $p < .001$) and does not have a significant impact on emotional support volume ($\beta = .01$, $p = .23$). Therefore, H3a and H3b are rejected.

H4a and H4b concern the mediating role of trust. Inconsistent with H4a, which predicts a positive mediation, trust negatively mediates the relationship between closure and information support volume ($\beta = -.003$, $p < .01$). Moreover, trust does not mediate closure and emotional support volume ($\beta = -.001$, $p = .18$). Therefore, H4a and H4b are rejected.

H5a and H5b predict the positive direct effect of closure on emotional support quality and speed, respectively. Inconsistent with the predictions, closure does not have a significant impact on emotional support quality ($\beta = .004$, $p = .73$). Although closure has a significant influence on emotional support speed, the direction is opposite to the prediction ($\beta = -.03$, $p < .05$). Thus, H5a and H5b are rejected.

H6a and H6b concern the mediating role of trust. Consistent with the prediction, trust mediates the relationship between closure and emotional support quality ($\beta = .003$, $p < .05$). However, trust does not mediate trust and emotional support speed ($\beta = .001$, $p = .15$). Therefore, H6a is supported, whereas H6b is rejected.

Research Question Testing

RQ1 asks if paths from network structure, social capital, to social support provision differ across the development stages of the OSG. To examine the research question, a coefficient-free multigroup model is compared with a coefficient-constrained multigroup model via the chi-square difference test. The two models have a significant difference such that the fit of a coefficient-free model is better than that of a coefficient-constrained model, indicating that path coefficients are moderated by the development stage of the OSG, χ^2 difference (48) = 136.39, $p < .001$. Thus, the relationships between network structure, social capital, and social support provision vary across the early, growth, and mature stages of the community. Table 5 summarizes path coefficients at different stages of the OSG.

The results show interesting patterns. The role of brokerage and non-redundant information in delivering information support is more effective in the later stages than in the early stage of the OSG. Although brokerage has a direct influence on the volume of information support provision in the early stage ($\beta = .137$, $p < .01$), the direct impact is not significant on information support uniqueness ($\beta = .052$, $p = .41$) and information support speed ($\beta = -.012$, $p = .83$). Moreover, non-redundant information does not mediate the impact of brokerage on information support volume ($\beta = .010$, $p = .19$), uniqueness ($\beta = -.002$, $p = .76$), and speed ($\beta = .018$, $p = .16$) in the early stage. However, the role of brokerage and its social capital becomes more important in conveying more effective information social support as the OSG grows and develops. In the growth and mature stage, information support volume is promoted by not only the direct effect of brokerage ($\beta_{growth} = .114$, $p_{growth} < .001$; $\beta_{mature} = .135$, $p_{mature} < .001$) but also indirectly through its social capital ($\beta_{growth} = .045$, $p_{growth} < .001$; $\beta_{mature} = .068$, $p_{mature} < .001$). Brokerage also has a direct impact on information uniqueness in the mature stage ($\beta = .050$, $p < .05$), and non-redundant information mediates the impact of brokerage on information uniqueness in the growth stage ($\beta = .033$, $p < .001$) and in the mature stage ($\beta = .027$, $p < .001$). Moreover, non-redundant information mediates the impact of brokerage on information speed in the mature stage ($\beta = .011$, $p < .05$).

The roles of closure and trust in promoting information and emotional support are nuanced and complex. As the results of hypotheses testing demonstrate, many results are nonsignificant or contradictory to the predictions. Nevertheless, some significant results indicate that closure has a positive direct impact on emotional support volume in the growth stage (β

= .072, $p < .001$). Moreover, the results indicate that the role of closure dynamically changes as the OSG grows. Closure has a positive direct impact on emotional support quality in the early stage ($\beta = .164$, $p < .001$), whereas the impact is negative in the growth stage ($\beta = -.057$, $p < .01$) and nonsignificant in the mature stage ($\beta = -.010$, $p = .61$).

DISCUSSION

The study examines social support provision behaviors in an online cancer community through the lens of social capital theory. The findings demonstrate that brokerage and non-redundant information promote diverse aspects of information support provision, whereas the roles of closure and trust are mixed in facilitating information and emotional support provisions. Although closure and trust facilitate provisions of high-quality emotional support, they have negative effects or do not have effects on other dimensions of social support. The results highlight the importance of considering the dynamic nature of OSGs by demonstrating that the impacts of network and social capital on support provision behaviors vary in accordance with the development stage of the OSG. The overall findings imply that social capital theory is a useful framework to understand the social path leading to information support provisions. The social mechanism of emotional support provisions is nuanced and complex in the context of OSGs.

Study Findings and Implications

The findings are consistent with previous studies arguing that people in a high brokerage position expand their knowledge and make informational contributions by taking advantage of non-redundant information (Kwon et al., 2020) (H1a–c and H2a–c). These findings substantiate that a bridging social connection or interaction enables people to experience non-overlapping information (Burt, 2007). Although social support literature suggests the benefits of OSGs for information support on the basis of the idea of weak ties (Wright & Bell, 2003), the empirical evidence supporting such argument is lacking; therefore, the concrete mechanism is unknown. The current study findings clearly explain why OSGs can be a good source for information support. OSGs can be a good source for information support, as people leverage the weak-tie nature of OSGs. By experiencing a non-redundant information environment, people in brokerage are able to provide community members with more, faster, and valuable information support.

Contrary to the study hypotheses, the closure structure and trust inhibit information support provision (H3a and H4a). The findings are inconsistent with the argument that closure structure mobilizes social help with a greater motivation (Granovetter, 1983; Wellman & Frank, 2017). It seems that the helping motivation derived from social relationships is not an adequate qualification for information support provision. In fact, relational intimacy does not guarantee information support provision (Adler & Kwon, 2002). Previous empirical evidence shows that relational properties (e.g., frequent interaction, trust, social identity) do not affect information support provision (Huang et al., 2019). Rather than relational closeness or strengths, knowledge or cognitive ability that can increase one's capacity for providing information may be a more important factor for information support provisions (Huang et al., 2019). Although individuals in a closure structure may have strong motivation to help others, they may not have the ability to do so presumably with their embeddedness in a redundant-information environment.

Closure facilitates provisions of high-quality emotional support via trust (H6a) rather than closure itself has a direct influence (H5a). Consistent with a previous study indicating that people in trustful relationships fulfil one another's needs of emotional support through caring and responsive communication (Weber et al., 2004), people who trust members of the OSG provide more emotionally responsive messages. Given that the quality of supportive message is associated with positive outcomes for recipients (High & Dillard, 2012), identifying what facilitates provision of a high-quality message is a critical issue in social support literature. The study finding is consistent with previous studies suggesting that relational factors affect the quality of emotional support (e.g., Costin & Jones, 1992). For instance, it was found that children are more emotionally responsive to a friend than an acquaintance (Costin & Jones, 1992). The current study expands the literature by suggesting trust as the underlying mechanism for emotional support provision of people in a close relationship. Moreover, the study findings imply the spillover effect of closure structure by demonstrating that trust initially formed in a closed network is generalizable to broader members in an online community (Pavlou & Gefen, 2004). Although the current study does not provide direct evidence, people may provide a higher quality of emotional support to members outside of their closed network through generalized trust.

Although trust plays a mediating role in facilitating a higher quality of emotional support, the effect was small. Moreover, many of the proposed research hypotheses concerning the closure structure and trust are rejected (H3b, H4b, H5b, H6a, and H6b), which imply the limited effects of closure and trust on emotional support provisions. Specifically, one should be cautious to overemphasize the role of closure and trust in promotion of emotional support in the context of OSGs. The restricted role of closure and trust may be ascribed to the weak-tie nature of OSGs. The descriptive statistics demonstrate that closure is not a common social structure at least in the studied OSG. In such a large open community where hundreds and thousands of contents are uploaded per day by numerous members, maintaining interactions with the same group of people would be challenging (Wright, 2000). Even if a closed network is built among members, the strength of ties in closure would be relatively too weak to maintain the closure structure for an extended time due to the weak-tie nature of OSGs (Wright & Bell, 2003). A previous study reported that participants from diverse OSGs found it difficult to seek support again from people they had interactions with before in OSGs (Wright, 2000). Given that closure can be easily broken with the dropout of at least one of the members in a closed network, maintaining a closure structure for an extended time could be extremely difficult in OSGs. The weak-tie nature of OSGs may make the closure structure fragile, which can further weaken the impacts of closure and trust on diverse aspects of emotional support.

Considering the weak-tie nature and the development stage of OSGs is helpful to understand the dynamic relationships among the network structure, social capital, and support provisions. The weak-tie nature of the OSG is enhanced with the development of the OSG (RQ1). In descriptive statistics, the increased degree centrality indicates that individual social exchange networks are diversified, and the brokerage index is also enhanced as the OSG develops. These increased network metrics imply that the weak-tie nature of the OSG is strengthened over time. However, the decreased density of the community and closure index evidence that the strengths of relationships among members may diminish over time as the community expands. The dynamic interplay between strengthened weak ties and weakened strong ties throughout the development stage of the OSG helps the interpretation of findings from RQ1. As the OSG develops from the early stage to the mature stage, the impacts of brokerage on information support provisions become stronger, whereas the impacts of closure on emotional support quality become weaker. As weak ties are strengthened from the early to the late stage, brokerage structure would become more effective in promoting information support in the late stage than in the early stage of OSGs. However, as strong ties are weakened from the early to the late stage, the effectiveness of closure structure in facilitating emotional support quality would diminish in the late stage than in the early stage. Although the findings demonstrate the dynamic in social mechanism of support provisions are interesting, they are far from being conclusive. Future studies are solicited to examine how the social dynamics in OSGs affect the roles of network and social capital in facilitating social support provisions.

Theoretical and Practical Contributions

The study makes several theoretical and practical contributions. The study contributes to social capital literature by demonstrating the benefits of distinguishing social capital explicitly from network structures. Despite the conceptual difference, many previous studies consider social capital equivalent to network structures (e.g., Huang et al., 2019; Meng et al., 2016; Shen et al., 2014). However, evidence suggests that network structure (e.g., brokerage) should not be used as a proxy for social capital (e.g., information diversity) as they are conceptually and empirically different (Graham et al., 2022). The conceptual reductionism that mingles network structure with social capital hinders us from delineating the theoretical path from the network structure to social capital and social capital to social behaviors. The current study findings substantiate that network structures and social capital are different, and distinguishing the two concepts benefit research by clarifying the theoretical paths to prosocial behaviors.

The study contributes to the current knowledge of the mechanism for social support provision by introducing the network perspective. Previously, the mechanism for social support provision remains at the perceptual (e.g., self-efficacy, empathy, and gender) (MacGeorge et al., 2005; Trobst et al., 1994) and dyadic levels (e.g., homophily and dyadic reciprocity) (Kordzadeh et al., 2014; Thoits, 1995). Although these studies provide valuable insights for understanding why people with certain characteristics or dyadic relationships facilitate support provisions, they provide an incomplete picture by ignoring the role of social context. By bridging social context to an individual behavior, the current study provides a more comprehensive understanding of how one’s social connection with other members in an OSGs provides social resources that one can utilize to help others informationally and emotionally.

The study improves social support literature by conceptualizing social support provisions as a multidimension concept. As opposed to other support concepts that have shown advancements in the conceptualization, the conceptual and operational definitions of social support provision have rarely been developed. As a result, most of previous studies consider only the quantity aspect of social support provision (e.g., Huang et al., 2019). Such a limitation could result in overlooking important mechanisms of support provisions. For instance, if the current study measured only the quantity of support provision, then the current study would not have been able to find the contribution of closure and trust on promoting the quality of emotional support. By integrating the quantity, quality, and timing aspects which altogether denote important behavioral information about support provision, the study provides fruitful implications for social support provision.

Practically, the study suggests the community administrators and community web designers to come up with ways to improve social connections among members on the basis of theoretical guidance and empirical evidence of social capital research. Given that the patterns of user interactions are substantially shaped and guided by the functions and services that OSGs provide, administrators and web designers have the ability to empower network configurations and social capital. For the sustainability of OSGs, it will be imperative for OSGs to balance weak and strong ties to promote both informational and emotional support provisions. Nevertheless, given the weak-tie nature of OSGs, OSGs may need to come up with features and services that can enhance strong-ties-based network structure (e.g., closure) and social capital (e.g., trust) among members. An example is providing a sub-community system where a small group of members can have intensive interactions on specific subjects.

Limitations and Future Study Directions

This study has limitations that provide directions for future studies. One limitation is focusing on a single communication channel (i.e., online support community) in examining social support behaviors. Given that people use multiple communication channels for social support exchange (Hlebec et al., 2006), this narrow observation would make social support behaviors occurring outside of the community platform unobservable. Moreover, people use different communication channels as their relationship with someone develops (Yang et al., 2014). Thus, an individual may use other personal communication channels for social support exchange as relationships with other members whom they meet in the community develop. Future studies need to integrate multiple communication channels that individuals use for social support exchange to gain a more comprehensive understanding of the role of networks and social capital in support provisions.

Another limitation is the study's sole reliance on social capital theory. Using a single theory improves the model parsimony, but it may drop the explanatory power of the model. Although social capital theory explains how social context plays a role in promoting social support provisions, it largely ignores perceptual-level factors such as self-efficacy and empathy that are known to play a critical role in facilitating social support provisions (Bar-Tal, 1986; MacGeorge et al., 2005). Given that social capital theory is less relevant to explain emotional support provisions in the context of OSGs, integrating social capital theory with other theories relevant to social support provisions may enhance our understanding of mechanisms of support provisions.

The study examined social support provisions in an online cancer community in an East Asian Country. This specific study context may not represent online support groups concerning other diseases in other countries. Social context and dynamics can vary depending on what types of diseases are concerned and what cultural values members share in OSGs. For instance, unlike cancer which has a low level of stigma in general (Vrinten et al., 2019), OSGs with stigmatized diseases (e.g., sexual diseases) may require stronger ties among members and display different social mechanisms for support provision behaviors. Moreover, given that social influences on prosocial behaviors vary across countries that have different cultural values (e.g., individualism and collectivism) (Saracevic et al., 2022), whether the influence of network and social capital on support provisions differ among those countries will be worth examining. Future studies are suggested to conduct cross-disease and cross-cultural studies to examine if the current study findings are replicable across different settings.

The study utilized a coarse temporal unit (i.e., a development stage) to investigate the dynamic changes in the social mechanism of social support provisions. This approach may fail to capture nuanced temporal changes among concerned variables over time. Moreover, comparing only three temporal stages (i.e., early stage, mature stage, and growth stage) will be insufficient to provide the overall dynamic patterns of social mechanisms for support provision behaviors. Thus, future studies are suggested to utilize a fine-grained temporal unit and employ other analytic models such as a time series model to overcome such limitations.

CONCLUSION

The current study investigated how network structures and social capital derived from networks promote information and emotional support provisions in OSGs. By utilizing computational methods, the study collected data from an online cancer community; measured network, social capital, and diverse dimensions of social support provisions; and examined the proposed research model. The findings demonstrate that the brokerage structure and non-redundant information promote the volume, uniqueness, and speed of information support provisions. Although the closure structure and trust facilitate a high quality of emotional support provision, the overall findings suggest that their impacts are limited in promoting information and emotional support provisions in the context of OSGs. Furthermore, the social mechanism from network to social capital and social capital to support provisions vary in accordance with the development stage of the OSG. The study contributes to existing literature by explicitly distinguishing social capital from network structure as well as by investigating their influences on diverse aspects of different types of support provision behaviors. Such elaboration of social mechanisms leading to information and emotional support provisions along with consideration of their dynamic nature enhances our understanding of theoretical associations between network, social capital, and social support provision.

APPENDICES

APPENDIX A: TABLES

Table 1

Different Types of Social Support Concepts

Concepts	Definitions	Operationalizations	Exemplar Studies
Social Embeddedness	Connections that individuals have to significant others in their social environments	- Presence of social ties - Frequency of contacts - Network metrics (e.g., density, reachability)	Eaton (1978); Snowden (2001)
Perceived Social Support	Cognitive appraisal of being reliably connected to others	- Perceived availability and adequacy	Seo et al. (2016)
Social Support Provision (Enacted Social Support)	Supportive actions and messages that an individual provides to others	- Count of supportive messages - The current study: count of supportive messages, semantic dissimilarity (uniqueness of information support), semantic similarity and message length (quality of emotional support), timing of support provision	Huang et al. (2019); Meng et al. (2016)

Table 2

Study Variables and Operationalizations

Variables	Operationalizations	Data Types
Dependent Variables		
Volume of ISP	The total number of ISP	-
Uniqueness of ISP	Averaged semantic independence between a focal person's ISP content and other ISP content across threads that a focal person participates in	Semantic
Speed of ISP	Averaged time difference between a focal person's ISP content and support-seeking content across threads that a focal person participates in	Temporal
Volume of ESP	The total number of ESP	-
Quality of ESP	Semantic similarity between a focal person's ESP content and support-seeking content is weighted by the length of the focal person's support provision content, then scores averaged to represent quality of ESP	Semantic
Speed of ESP	Averaged time difference between a focal person's ESP content and support-seeking content across threads that a focal person participates in	Temporal
Independent Variables		
Brokerage	Weighted betweenness centrality	Relational
Closure	Weighted local clustering coefficient	Relational
Mediators		
Non-redundant Information	Averaged semantic independence across messages that a focal person is exposed to	Semantic
Trust	The proportion of self-disclosed words in contents that a focal person updated	Semantic
Controls		
Post activities	The number of posts that a focal person uploaded during the study period	-

Note. ISP = Information Support Provision; ESP = Emotional Support Provision

Table 3

Summary of Network Statistics across the Panel

Study Time	Community Level		Individual Level		
	Network Size	Density	Brokerage[a]	Closure[a]	Degree Centrality
Early	580.885	0.008	792.018	0.013	7.390
Growth	4282.75	0.002	9433.355	0.002	11.418
Mature	6941.50	0.001	15293.022	0.002	12.452
1 (2009 Spring)	260	0.022	232.577	0.019	10.269
2 (2009 Fall)	466	0.011	564.951	0.026	9.953
3 (2010 Spring)	490	0.008	625.667	0.013	7.841
4 (2010 Fall)	581	0.005	832.336	0.014	5.580
5 (2011 Spring)	522	0.005	787.643	0.007	5.406
6 (2011 Fall)	619	0.004	923.678	0.008	5.121
7 (2012 Spring)	915	0.003	1271.526	0.011	5.766
8 (2012 Fall)	794	0.006	1097.769	0.008	9.181
9 (2013 Spring)	2204	0.002	4601.795	0.003	9.770
10 (2013 Fall)	3059	0.002	6182.873	0.003	12.246
11 (2014 Spring)	3343	0.002	7134.300	0.002	12.638
12 (2014 Fall)	4848	0.001	10624.957	0.003	11.643
13 (2015 Spring)	6416	0.001	15202.691	0.002	9.719
14 (2015 Fall)	7473	0.001	17296.254	0.002	9.628
15 (2016 Spring)	3351	0.002	6764.918	0.001	13.375
16 (2016 Fall)	3568	0.002	7659.051	0.002	12.327
17 (2017 Spring)	5310	0.001	10817.343	0.002	13.114
18 (2017 Fall)	6369	0.001	13610.065	0.002	12.989
19 (2018 Spring)	7509	0.001	17355.850	0.002	12.211
20 (2018 Fall)	8578	0.001	19388.830	0.002	11.492

Note. Statistics of the early stage are obtained by averaging statistics of panels 1–8 in study time; statistics of the growth stage are obtained by averaging statistics of panel study time 9–16 in study time; and statistics of the mature stage are obtained by averaging statistics of panel 17–20 in study time. The first batch of each panel data (January–March or September–November) is used for the descriptive statistics.

a. Raw scores of brokerage and closure are reported. Log-transformed scores of brokerage and closure are used in the main analysis.

Table 4

Summary of Hypotheses Testing

Hypotheses	Relationships	Beta	Supported?
H1a	Bro → Info Volume	$.134^{***}$	Yes
H1b	Bro → Info Unique	$.036^{*}$	Yes
H1c	Bro → Info Speed	.020	No
H2a	Bro → Non-redundant → Info Volume	$.054^{***}$	Yes
H2b	Bro → Non-redundant → Info Unique	$.027^{***}$	Yes
H2c	Bro → Non-redundant → Info Speed	$.010^{**}$	Yes
H3a	Clo → Info Volume	$-.054^{***}$	No
H3b	Clo → Emo Volume	.011	No
H4a	Clo → Trust → Info Volume	$-.003^{**}$	No
H4b	Clo → Trust → Emo Volume	−.001	No
H5a	Clo → Emo Quality	.004	No
H5b	Clo → Emo Speed	$-.028^{*}$	No
H6a	Clo → Trust → Emo Quality	$.003^{*}$	Yes
H6b	Clo → Trust → Emo Speed	.001	No

R-squared Values of Variables	
Info Volume	.228
Info Unique	.010
Info Speed	.003
Emo Volume	.091
Emo Quality	.007
Emo Speed	.011
Non-redundant	.068
Trust	.016

Model Fit	
Chi-square (*df* = 87)	606.03^{***}
CFI	.92
RMSEA	.06
SRMR	.04

Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Bro = Brokerage; Info Volume = Information Support Volume; Info Unique = Information Support Uniqueness; Info Speed = Information Support Speed; Non-redundant = Non-redundant Information; Clo = Closure; Emo Volume = Emotional Support Volume; Emo Quality = Emotional Support Quality; Emo Speed = Emotional Support Speed

Table 5

Path Coefficients at the Early, Growth, and Mature Stage of the OSG

Relationships	Early Stage (n = 343)	Growth Stage (n = 2,178)	Mature Stage (n = 2,765)
Bro → Info Volume	$.137^{**}$	$.114^{***}$	$.135^{***}$
Bro → Info Unique	.052	.017	$.050^{*}$
Bro → Info Speed	−.012	.014	.035
Bro → Non-redundant → Info Volume	.010	$.045^{***}$	$.068^{***}$
Bro → Non-redundant → Info Unique	−.002	$.033^{***}$	$.027^{***}$
Bro → Non-redundant → Info Speed	.018	.003	$.011^{*}$
Clo → Info Volume	$−.109^{*}$	$−.088^{***}$	$−.053^{**}$
Clo → Emo Volume	−.051	$.072^{***}$	.021
Clo → Trust → Info Volume	−.019	-.003	-.003
Clo → Trust → Emo Volume	.001	−.0003	−.001
Clo → Emo Quality	$.164^{**}$	$−.057^{**}$	−.010
Clo → Emo Speed	$−.132^{**}$	−.009	−.008
Clo → Trust → Emo Quality	−.0003	.002	.003
Clo → Trust → Emo Speed	−.0003	.0002	.001
R-squared Values of Variables			
Info Volume	.234	.194	.219
Info Unique	.004	.020	.014
Info Speed	.077	.003	.006
Emo Volume	.162	.099	.059
Emo Quality	.031	.008	.018
Emo Speed	.029	.004	.006
Non-redundant	.065	.108	.131
Trust	.024	.002	.005
Model Fit			
Chi-square (*df* = 39)		469.63^{***}	
CFI		.93	
RMSEA		.08	
SRMR		.03	

Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

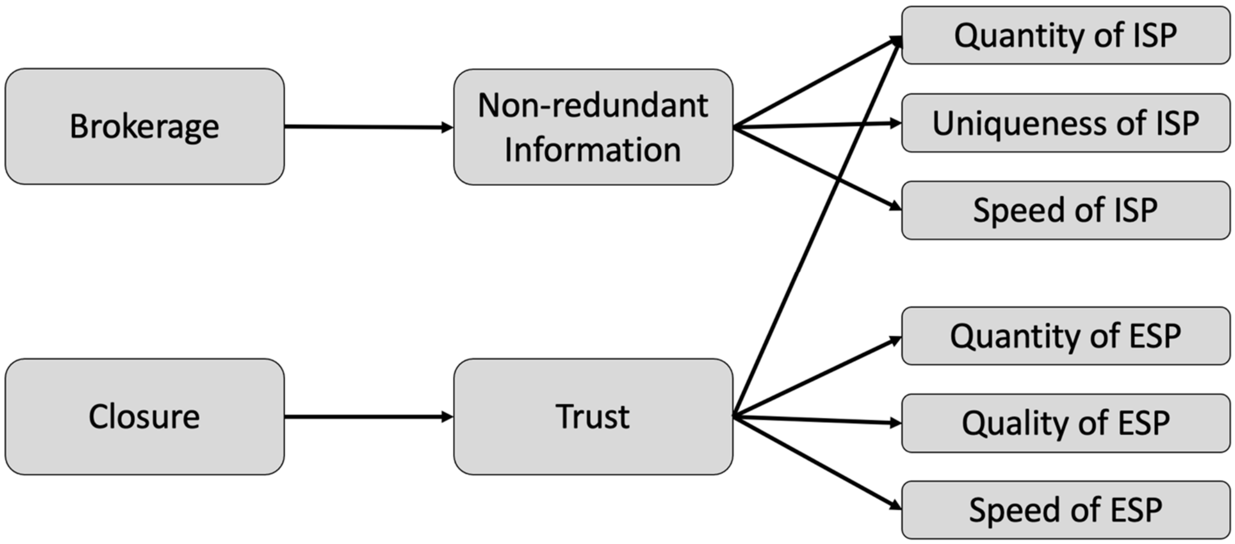
Bro = Brokerage; Info Volume = Information Support Volume; Info Unique = Information Support Uniqueness; Info Speed = Information Support Speed; Non-redundant = Non-redundant

Information; Clo = Closure; Emo Volume = Emotional Support Volume; Emo Quality = Emotional Support Quality; Emo Speed = Emotional Support Speed

APPENDIX B: FIGURES

Figure 1

Proposed Research Model



Note. ISP = Information Support Provision; ESP = Emotional Support Provision

Figure 2

Study Design

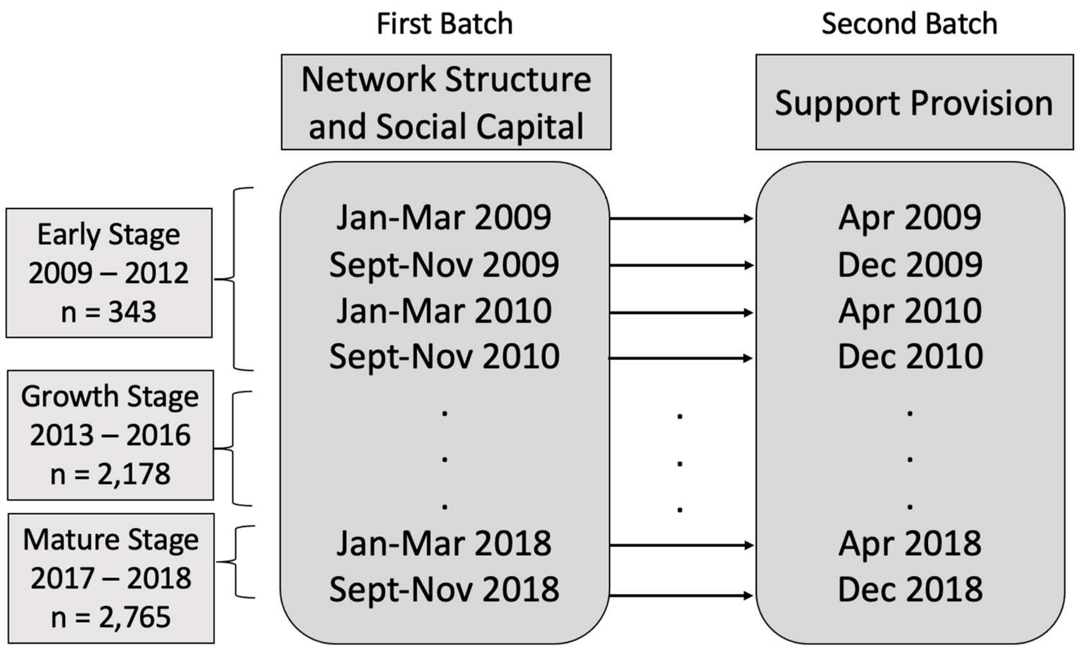
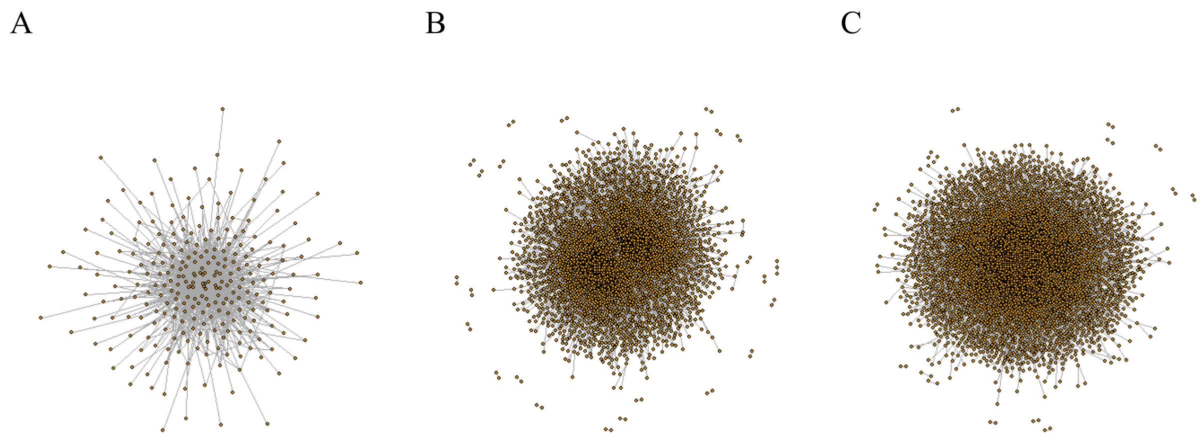


Figure 3

Examples of Support Exchange Network at the (A) Early, (B) Growth, and (C) Mature Stage of the OSG



Note. Graphs A, B, and C are networks from the 2009, 2014, and 2017 spring panels of the first batch (January–March), respectively. Nodes are members and edges are interactions among members.

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