Front. Eng. Manag. 2025, 12(4): 1094–1123
https://doi.org/10.1007/s42524-025-4222-z

RESEARCH ARTICLE

Shanshan GUO, Xitong GUO, Xinghan WU, Gongpu HE, Kaichao WANG

Enhancing social support: Role of professional capital in shaping identity-driven participation in online patient communities

Abstract An online patient support community (OPSC) facilitates information exchange and emotional support among patients with shared health conditions. While the benefits of OPSCs for patients' physical and mental well-being are well-documented, the antecedent factors that drive patients to provide informational and emotional support remain underexplored. This study extends social identity theory to investigate how professional capital—comprised of human capital, decisional capital, and social capital—affects the provision of social support in OPSCs. The study also examines how identity rights, representing community status and privileges, moderate this relationship. An empirical study was conducted on one of the largest diabetes OPSCs in China, analyzing 227,901 text interactions from 5,977 members. Using text mining analytics (i.e., text classifiers and latent Dirichlet allocation models), we measured professional capital and examined its influence on social support provision. The results reveal that professional capital significantly impacts the provision of both informational and emotional support. Specifically, the human and decisional dimensions of professional capital exert a stronger influence than the social dimension. Additionally, identity rights positively moderate the effects of professional capital on social support provision, showing that members with higher status and privileges contribute more actively. These findings have important implications for both management theory and practice.

Keywords online patient support community, social support, professional capital, text mining

Received Nov. 11, 2024; revised May 20, 2025; accepted Jul. 22, 2025

Shanshan GUO, Kaichao WANG
School of Business and Management, Shanghai International Studies University, Shanghai 201620, China

Xitong GUO (✉), Xinghan WU (✉), Gongpu HE
School of Management, Harbin Institute of Technology, Harbin 150001, China
E-mails: xitongguo@hit.edu.cn; xinghanwu@hit.edu.cn

This research was supported by the National Natural Science Foundation of China (Grant Nos. 72171152, 72125001, 72431004, 72441024, 72293584, and 72121001); the Scientific and Technological Innovation (Soft Science) of Shanghai, China (No. 24692115400); and the Fundamental Research Funds for the Central Universities (No. 2023TD003).

1 Introduction

An online patient support community (OPSC) functions as a digital refuge for individuals facing similar health challenges, providing a platform where patients can both seek and offer support within a virtual collective (Coulson, 2013; Frost and Massagli, 2008; Kazmer et al., 2014). Leveraging information and communication technology, OPSCs facilitate virtual social interactions, enabling patients to form friendships, exchange health information, share their illness experiences, and provide emotional support (Guo et al., 2016; Shaw et al., 2000; Wright et al., 2003). The primary appeal of OPSCs lies in their ability to connect patients with peers who have undergone similar journeys, thus fostering the exchange of empathetic support and shared experiences (Liu et al., 2020; Yang et al., 2019). Such exchanges can be less readily available through traditional sources like family members or healthcare professionals, who may not share the same lived experiences (O'Neill et al., 2014) .

Social support, defined as the assistance exchanged through interpersonal connections within social networks (Cohen et al., 2000; Yan and Tan, 2014), is widely recognized as a significant benefit of patient participation in OPSCs (Dang et al., 2021). Previous research on social support provision has primarily focused on two perspectives: that of the recipient and that of the supporter (Wright et al., 2003; Yan and Tan, 2014). From the recipient's viewpoint, individual traits—such as empathy needs, privacy concerns, autonomy, and demographic factors (e.g., age, gender, race)—can influence their ability to build relationships and effectively seek support (Barak et al., 2008; Rains and Young, 2009). Conversely, studies on supporters' motivations have examined internal factors (e.g., compassion, dedication, desire for self-worth) and external rewards (e.g., social or economic gains) as drivers of social support behaviors (Dang et al., 2024).

However, interactions within these communities extend beyond simple transactions of emotional or informational support. A more dynamic process emerges, wherein experienced patients—those with long-term illness experiences—draw upon their accumulated medical knowledge and expertise. This accumulated knowledge is conceptualized as "professional capital," (Hargreaves and Fullan, 2015) referring to the knowledge, skills, and experience individuals gather through prolonged engagement in a specific domain (Guo et al., 2017). In OPSCs, professional capital mirrors the expertise traditionally attributed to healthcare providers. Importantly, this capital not only enables patients to offer valuable support but also significantly enhances their identity and social status within the community, allowing them to assume more authoritative and supportive roles. Therefore, there exists a gap in the literature regarding how patients' professional capital which resulting their community identities influence their provision of social support in OPSCs.

Drawing on Social Identity Theory (SIT) (Van Dick, 2001), we argue that the professional capital accumulated by patients through their ongoing experiences with illness strengthens their self-concept and reinforces their identity within the OPSC. This reinforced identity not only boosts patients' commitment to the community but also motivates them to take on more proactive roles in providing support to others (Davis et al., 2019). As patients become more integrated within the community, their contributions are recognized, elevating their standing as valuable members whose knowledge and experience are esteemed. This identity-driven engagement thus signifies personal growth and transforms the patient into a key contributor within the OPSC.

This study aims to explore how professional capital, as the concrete manifestation of social identity in a professional context, shapes the dynamics of social support within OPSCs. We hypothesize that as patients increasingly view themselves as informed and knowledgeable contributors, they become more inclined to engage in behaviors that benefit the entire community. This perspective shifts the focus from solely internal or external motivations to a broader understanding of the diverse roles patients play within these communities.

To investigate these dynamics, we employ a methodological approach that utilizes text mining analytics and econometric techniques to quantify both social support and professional capital from the extensive text data generated within OPSCs. This approach addresses the challenges inherent in measuring abstract constructs like social support and professional capital, providing a nuanced understanding of patient motivations and behaviors within these digital environments

The findings of this research have significant implications, offering valuable insights into the mechanisms that drive social support in OPSCs and suggesting strategies to enhance community engagement and support provision. By examining the roles of professional capital and identity in shaping patient behavior, this study contributes to the development of more effective interventions and platforms designed to foster vibrant and supportive community environments.

2 Literature

2.1 Online patient support communities

Current research on OPSCs can be categorized into three main perspectives: information, users, and communities. Studies within these perspectives tend to focus on interaction content, communication quality, privacy concerns, and participant relationships. Additionally, research has explored the relationships between OPSC mechanisms—such as ease of use, privacy, and trust mechanisms—and user engagement, including participant behaviors and sharing intentions (see Table 1 for details).

Despite the recognized role of OPSCs in providing social support and promoting health recovery, the current design of community functions and interaction mechanisms does not fully stimulate patients' social support behaviors. Furthermore, community management strategies require improvement (Guo et al., 2018). To enhance the OPSC service process and ensure sustainable development in the Web 2.0 environment, a deeper understanding of how to study social support behaviors within OPSCs is necessary. This includes the scientific design of incentive mechanisms to encourage social support provision and the effective management of community participants (Shinn et al., 1984).

2.2 Social support in OPSCs

Social support refers to the assistance exchanged through social relationships and interpersonal communication (Cobb, 1976; Cohen et al., 2000; Sarason et al., 1983). As a critical element of social life, social support has been extensively studied in sociology, psychology, and communication. Generally, social support involves supportive interactions embedded within interpersonal relationships, where resources are exchanged between support providers and recipients (Lekwijit et al., 2024; Shumaker and Brownell, 1984). The primary goal of these exchanges is to enhance the well-being of the recipient. The resources exchanged in these interactions can be material goods or services, information, or emotional

Table 1 Research on online patient support communities

Research perspective	Research subdivision	Main research content/viewpoint	Studies
Information perspective	Information content	The knowledge sharing willingness of members in the OPSCs is affected by altruism, centrality of interaction, sense of belonging, etc.	Yang et al., 2021
		Different tools in OPSCs encourage users to provide different kinds of social support	Chuang and Yang, 2010
		The text in the OPSCs can be divided into informational support, emotional support and companion support	Wu et al., 2017
	Information quality	In terms of content value and social emotional support, clarity, completeness, accuracy and operability are important factors that affect OPSC content quality	Zhao et al., 2021
		Privacy computing has an important impact on OPSC use intention	Dang et al., 2020
		Privacy concerns significantly negatively affect OPSC users' willingness to disclose health information	Alemu and Huang, 2020
		The dimensions of good faith trust, ability trust, and honesty trust all positively affect the behavior of patients in OPSCs	Jin et al., 2021
	Information privacy	User knowledge sharing networks in OPSCs have scaleless property and small-world effects	Zhang et al., 2017a
		Most OPSC users are at the edge of social networks, accepting social support instead of actively providing	Stewart and Abidi, 2012
User perspective	User relationship	Different types and sources of social support and gamification factors affect the continuous participation behavior of OPSC members	Song et al., 2018
		Perceived usefulness and patient satisfaction comprehensively affect users' continued use of OPSCs	Wu, 2018
	User behavior	Patients can benefit from the learning of others, and their participation in OPSCs can help them improve their health and better participate in the disease self-management process	Yan and Tan, 2014
		Knowledge sharing, experience sharing and spiritual support are the main contents of health information exchange among OPSC users	Tamjidyamcholo et al., 2014
Community perspective	Community value	OPSC is a typical medical service innovation, but the system design and community management still need to better meet the needs of users	Chen et al., 2020b

support (Guo et al., 2025).

Previous research has identified various categories of social support. For instance, social support is often classified into instrumental, emotional, and informational support (Chen and Feeley, 2014; Helgeson, 2003; Zhou et al., 2023). Instrumental support refers to tangible resources, such as financial, material, time, or labor assistance (King et al., 2006). In healthcare, this may include medical environments, devices, and services like physical examinations or tests. Informational support involves the exchange of knowledge, suggestions, and problem-solving advice, which can reduce uncertainty for the recipient (Liao et al., 2024; Wu, 2018). In healthcare, informational support encompasses general knowledge, experience, guidance, and rehabilitation advice (Zaphiris and Ang, 2009; Zhao et al., 2021). Emotional support, on the other hand, includes encouragement, sympathy, and appreciation, often exchanged between doctors and patients (Alemu and Huang, 2020; Huang et al., 2013). Available evidence suggests that instrumental support is the least visible type of support within OPSCs (Blank et al., 2010), largely it often requires physical presence to provide tangible resources, such as financial aid or material goods (e.g., medical devices), which are difficult to deliver in virtual settings where participants are geographically dispersed (Zaphiris and Ang, 2009). For example, logistical barriers (e.g., shipping costs) and privacy concerns (e.g., disclosing financial information) further limit the feasibility of instrumental support, even when community members express willingness to assist. In contrast, informational and emotional support, which address problem-solving and emotional needs, respectively, are more prevalent in OPSCs (Rains et al., 2015). Thus, this study focuses on these two key subtypes of social support: informational and emotional.

Extensive research has also explored social support provision in various domains and scenarios. Social support provision is influenced by recipient and supporter characteristics, as well as the structure of the interaction network Therefore, it is essential to examine not only the needs of the recipients and the motivations of the supporters but also the influence of the network structure between them. A summary of relevant studies on social support in online communities is provided in Table 2.

Existing research on online communities highlights informational and emotional support as the dominant forms of social support in OPSCs. While many studies have examined factors influencing social support provision—such as social interaction and the community environment—most research approaches these factors from a narrow perspective, focusing on either recipient or supporter characteristics, or specific aspects of network structures. Few studies have undertaken a comprehensive analysis of social support provision from a broader social network perspective. Thus, there is a need for more holistic research that examines how network structures, in conjunction with individual characteristics, influence the provision of social support in OPSCs.

Table 2 Research on social support in online communities

Research perspective	Research subdivision	Main research content/viewpoint	Studies
The impact of social support on health	Informational support	There is a positive correlation between the informational support network of patients and self-management ability, especially among those with a low level of education	Koetsenruijter et al., 2016
		Social support influences users' health knowledge contribution and acquisition behavior through social capital	Zhou, 2020
	Emotional support	Unlike traditional face-to-face emotional support, social media-based emotional support is associated with a higher risk of depression	Shensa et al., 2020
		Online emotional support is related to the improvement of blood glucose in patients with diabetes mellitus	Turner et al., 2013
Influencing factors of social support	Support demand side	The degree of emotional disclosure has a positive effect on obtaining support from others	Yang et al., 2018
		Narrative expression helps to form close contact with the audience and promote social support response	Hale et al., 2018
	Support provision side	The engagement of online health communities helps to meet the internal and external motivations of supporters	Carron-Arthur et al., 2015
	Network structure	The language style matching between two individuals may promote their emotional and informational support for each other	Rains, 2016
		Online support communities reduce the stigmatization of disease among members and make them more willing to provide social support	Wright, 2016

3 Theories and hypotheses

3.1 Social identity theory

Social Identity Theory (SIT) was first proposed by Tajfel (1974) and has since been widely researched and applied in fields such as management, sociology, and psychology (Davis et al., 2019; Vahtera et al., 2017). Social identity refers to an individual's identification with a particular social group and is composed of three key components: cognitive, evaluative, and emotional (Van Dick, 2001). When a person identifies with a group, they automatically adopt that group's social identity.

SIT explains that individuals naturally categorize others as either in-group (us) or out-group (them). According to SIT, social identity is a distinct part of self-concept. People classify themselves at different levels: at the individual level, they perceive themselves as unique individuals, focusing on personal characteristics that distinguish them from others (Van Dick et al., 2005). For instance, when someone is thinking at the individual level, they might describe themselves as conscientious. This form of identity emphasizes in-group comparisons and personal recognition. At the group level, individuals view themselves as part of a larger group, highlighting differences between their group and others. For example, someone who identifies as part of a soccer team may describe themselves as cooperative and passionate, traits commonly associated with their in-group. This group identity involves comparing groups and reflects the degree to which an individual aligns with their group.

The stronger an individual's sense of belonging to a group, the higher their social identity. People not only seek to belong to groups, but they also prefer to be part of groups that are positively perceived. This desire motivates individuals to form groups quickly and show favoritism toward their in-group (Suhay, 2015). SIT suggests that the more closely an individual feels connected to their in-group, the more accepted they feel by its members, which in turn increases their affection for the group and their willingness to engage in pro-group behaviors.

Based on SIT, individuals with stronger identification with their communities are more likely to engage in pro-social behaviors to reinforce group cohesion and self-worth. In the context of OPSCs, the development of professional capital (comprised of human, social, and decisional resources) serves as a personal foundation for members to enact their identity and contribute to the collective. Meanwhile, symbolic recognitions in the form of identity rights further shape how individuals transform personal resources into social support behaviors. Therefore, in the following sections, we operationalize the core concepts derived from SIT and propose how they influence members' engagement in informational and emotional support provision.

3.2 The effect of professional capital on social support

Drawing from SIT, we argue that the accumulation of professional capital enables members to reinforce their social identity within the community. As members gain recognition for their human, social, and decisional capabilities, they are more likely to perceive themselves as valuable contributors to the group. This reinforced identity, in turn, motivates them to engage in social support behaviors, particularly in providing informational and emotional assistance to others. In this section, we define the dimensions of professional capital and examine their effects on social support provision.

SIT emphasizes the recognition of personal identity and how individuals distinguish themselves from others. In the context of OPSCs, most participants are patients who have been dealing with specific illnesses over extended periods. Through continuous treatment and personal experience, these patients develop a deep understanding of their conditions, including the mechanisms of their diseases, the effects of medications, and various treatment processes. This ongoing engagement allows them to accumulate professional capital, similar to the expertise that healthcare professionals, such as doctors, acquire through formal training. As these patients develop professional capital within the OPSC, they also begin to recognize their unique position within the group. This recognition reinforces their identity within the community, motivating them to actively contribute to the group's well-being. Specifically, patients with greater professional capital often take on the role of informal experts, offering informational support in the form of knowledge and treatment advice, while also providing emotional support through shared empathy and experience (McCaig et al., 2019; Zhu et al., 2020).

Professional capital was originally introduced by Hargreaves and Fullan (2015) in the field of education. It refers to the resources or attributes that professionals accumulate through education, social practice, and certification in their respective fields. This form of capital is typically rare, valuable, and long-lasting, often associated with professions like teaching, medicine, and law (Fullan et al., 2015). Professional capital is composed of three dimensions: human capital, social capital, and decisional capital (Hargreaves and Fullan, 2013).

The **human capital dimension of professional capital (HCPC)** refers to the abilities, skills, knowledge, and experience individuals possess. In the context of OPSCs, patients accumulate status by being recognized as knowledgeable and reliable sources of information within the community.

The **social capital dimension of professional capital (SCPC)** involves the recognition and trust that emerge from collaboration and relationships within a community. Patients build social capital by establishing stable, trusting relationships with other members and cultivating a strong sense of belonging within the professional group.

The **decisional capital dimension of professional capital (DCPC)** refers to the ability and willingness of individuals to make sound judgments based on their expertise. In OPSCs, patients develop decisional capital through their capacity to make informed health-related decisions, which are shaped by their accumulated experiences and interactions with healthcare providers (Guo et al., 2017).

Together, these three dimensions of professional capital contribute to the improvement of a patient's self-identity. According to SIT, as patients in OPSCs develop a doctor-like identity, they are motivated to engage in pro-group behaviors, such as providing information and emotional support to others. In this way, their professional capital enhances their ability to support the community, positioning them as key contributors to the well-being of other members.

3.2.1 The effects of HCPC on social support

Human capital in professional capital (HCPC) refers to the knowledge, skills, experience, and abilities that individuals acquire in a specific domain. In the context of professional fields like healthcare, HCPC is typically accumulated through formal education, certifications, and practical experience. However, in OPSCs, where patients lack these formal markers, HCPC is instead reflected in the ability to effectively communicate using shared language and specialized healthcare knowledge derived from their lived experiences. This includes both the common language that community members develop based on shared experiences and the professional language that indicates their knowledge and understanding of healthcare processes (Nahapiet and Ghoshal, 1998; Wasko and Faraj, 2005).

HCPC thus includes both a shared communication framework and specific expertise that help community members express themselves and share information. Patients who possess knowledge of healthcare treatments, side effects, and disease mechanisms are more likely to relate to one another within the community than to healthcare professionals or even family members. This ***common language***, composed of consistent terms, topics, and communication patterns, not only represents the collective culture of the community but also ensures that conversations are cohesive and mutually understood (Argyle, 1978). Mastering this language allows members to engage more deeply in community discussions and support exchanges (Galegher et al., 1998). Moreover, the ***professional knowledge*** they acquire, although informal, enhances their ability to contribute meaningfully to the community (Ardichvili et al., 2003).

As members' healthcare knowledge deepens, they become more adept at interpreting complex medical information and providing well-informed responses, improving the overall quality of communication within the community (Huang et al., 2014). This professional capital also fosters informational support, as members who can use specific healthcare terminology are better equipped to efficiently share their knowledge and experiences (Nonnecke and Preece, 2003). The use of shared language reduces communication barriers and increases the effectiveness of information exchange, which enhances the overall communication process (Butler, 2001). Additionally, individuals with higher HCPC are more likely to recognize the needs of others and respond by offering valuable advice and insights, such as experiences with medication or treatment options (Mao and Benbasat, 2000). Based on this reasoning, we propose the following hypothesis:

H1a: The HCPC of OPSC members positively affects their provision of informational support.

HCPC also influences the provision of emotional support. Individuals who have gained extensive HCPC through their experiences and interactions in the community are often more empathetic and capable of offering encouragement and emotional care to others (Håkansson and Montgomery, 2003). As patients share emotional experiences in the common language of the community, they develop a better understanding of each other's emotional expressions and can provide empathetic responses. This shared language not only strengthens emotional bonds within the community but also ensures that members are attuned to each other's feelings and able to offer relevant emotional support. Therefore, the higher a member's HCPC, the greater their ability to understand the emotional states of others and provide meaningful emotional support. Therefore, we propose the following hypothesis:

H1b: The HCPC of OPSC members positively affects their provision of emotional support.

3.2.2 The effects of SCPC on social support

In the context of OPSCs, social capital dimension in professional capital (SCPC) plays a crucial role in shaping how members interact, share information, and provide emotional support. SCPC reflects the social relationships and networks that emerge from members' ongoing interactions, and it is influenced by two key dimensions: ***community trust*** and ***community identity*** (Granovetter, 1985). These dimensions are essential for understanding how patients who accumulate professional capital through lived experiences rather than formal qualifications contribute to social support within the community.

Community trust is fundamental in OPSCs because members frequently share sensitive personal and health-related information. Community trust refers to an individual's confidence that others will protect their privacy, respect the shared information, and act responsibly (Dinev and Hart, 2006; Ommen et al., 2011). In OPSCs, where members are non-professionals, community trust in the confidentiality of shared information and the reliability of advice from other patients is critical (Jiang et al., 2011; Pavlou and Gefen, 2004; Wright et al., 2003). Without community trust, members may hesitate to share important health insights, which could otherwise contribute to the community's collective knowledge and support (Andrews and Delahaye, 2002; Tsai and Ghoshal, 1998). Community trust thus facilitates both informational and emotional support, as members feel safe sharing knowledge and expressing vulnerability.

Community identity is the second key component of SCPC. It refers to the emotional connection members feel toward the community, which fosters a sense of belonging and responsibility (Ellemers et al., 2004; Knippenberg, 1991). In OPSCs, community identity is strengthened by shared health experiences, which create a sense of solidarity among members (Hogg and Terry, 2000). This identity motivates individuals to actively participate, share knowledge, and provide emotional support to others (Brashers et al., 2004). When members feel a strong connection to the community, they are more likely to offer informational support by contributing their expertise and emotional support by empathizing with others' experiences and challenges (Wright et al., 2003).

Together, community trust and community identity create a supportive environment where patients, drawing on their professional capital, can provide both informational and emotional support. Community trust ensures that members feel comfortable sharing their experiences and knowledge, while community identity encourages them to contribute actively to the collective well-being of the group. Based on this understanding, we propose the following hypotheses:

H2a: SCPC of OPSC members positively affects their provision of informational support.

H2b: SCPC of OPSC members positively affects their provision of emotional support.

3.2.3 The effects of DCPC on social support

DCPC refers to the ability and willingness of OPSC participants to make sound judgments based on their accumulated experience and knowledge (Guo et al., 2017). In the context of OPSCs, DCPC is reflected through members' decision-making capabilities, which are manifested in both the frequency and intensity of their interactions. High ***interaction frequency*** and ***interaction intensity*** signify the degree to which members engage with the community and demonstrate their decision-making skills through continuous contributions to discussions. These interactions also reflect members' willingness to participate, contribute to others' well-being, and reinforce their identification with the "doctor-like" role within the community.

Interaction frequency refers to how often members engage with the community, which indicates their decision-making speed and readiness to offer support (Nahapiet and Ghoshal, 1998). Interaction intensity, on the other hand, represents the depth and quality of the information exchanged, showing how thoroughly members engage in problem-solving and support discussions (Wellman, 1989). High interaction frequency and intensity are expressions of decisional capital, where members frequently offer judgments on health-related issues and take active roles in assisting others, embodying the spirit of contribution and leadership (Ryan et al., 2005).

Members with high DCPC, as indicated by their frequent and deep interactions, are better equipped to provide informational support (Yli-Renko et al., 2001). Their decision-making capabilities, honed through regular participation and knowledge-sharing, allow them to assess the quality and relevance of the information they encounter. As they engage in more discussions, they become proficient at offering accurate, timely, and contextually relevant advice, whether it's about treatment options, medication management, or general health strategies (Kawachi and Berkman, 2001). Their frequent involvement allows them to recognize others' informational needs quickly and respond with practical advice, making them key contributors to the community's collective knowledge. Therefore, we propose the following hypothesis:

H3a: *DCPC of OPSC members* positively a*ffect their provision of informational support.*

In addition to enhancing informational support, high DCPC also facilitates the provision of emotional support. The frequent and intensive interactions foster empathy and emotional understanding. Members with high DCPC have likely navigated similar emotional challenges themselves, which allows them to offer emotional reassurance, encouragement, and validation to others in the community. Their decision-making process includes not only the ability to provide factual information but also the judgment of when emotional support is necessary (Brown and Duguid, 2001). Members who engage deeply with others are more attuned to the emotional states of their peers and more capable of providing the kind of support that fosters emotional well-being and strengthens community bonds (Wright et al., 2003). Based on these insights, we propose the following hypothesis:

H3b: DCPC of OPSC members positively affects their provision of emotional support.

3.3 The moderating effect of identity rights

While professional capital provides the foundation for community members to engage in social support, this relationship may be conditioned by members' level of symbolic integration into the group. In online communities, such symbolic integration is often reflected through identity rights, privileges and recognitions granted by the platform or peer members. These rights reinforce members' perceived legitimacy and visibility, thus amplifying the identity-expressive function of professional capital. We next explore how identity rights moderate the impact of professional capital on social support behaviors.

The group level of SIT emphasizes the extent to which individuals identify with their group. The stronger an individual's identification with a group, the more willing they are to use their strengths to help the group. Prior research demonstrates that individuals who strongly identify with an organization are more likely to adopt the organization's goals as their own and exhibit loyalty and commitment (Dutton et al., 1994). Moreover, social identity has been shown to increase users' willingness to contribute knowledge (Kim et al., 2011; Wang and Wei, 2011). In the context of OPSCs, members are patients who face similar health challenges, leading to a strong sense of belonging within the community. This sense of belonging motivates them to use their personal attributes and resources to provide assistance to others.

In virtual communities, identity rights refer to the permissions and privileges that members gain as they become more integrated into the community. These rights include access to advanced features, such as enhanced privacy settings, the ability to add multimedia content to posts, personalized search options, and other tools that enhance engagement. As members gain identity rights, they also acquire greater responsibility within the community. Research shows that users with stronger community identity and influence are more likely to leverage their professional capital to contribute to the group (Child, 2016). The extent of identity rights may regulate how effectively members can access resources and engage with others. Higher identity rights grant members more capabilities to contribute, while lower rights may limit their ability to fully participate in community activities.

Members with extensive identity rights often have greater trust and recognition within the community, increasing their likelihood of utilizing their professional capital to provide both informational and emotional support. In contrast, members with fewer identity rights may feel less obligated to transform their professional capital into social support. Therefore, members with higher identity rights are more likely to actively participate in the community, using their professional capital to assist others through the provision of support. Based on these insights, we propose the following hypotheses:

H4a: The identity rights of OPSC members positively moderate the effect of professional capital on the provision of informational support.

H4b: The identity rights of OPSC members positively moderate the effect of professional capital on the provision of emotional support.

Based on the influential factors discussed in this section, we constructed a research model that frames the effects of HCPC, SCPC, and DCPC on the provision of informational support and emotional support by OPSC members. Additionally, to control for factors that may influence the provision of social support, this study includes two control variables: community tenure, which reflects the duration of participation in the community, and external incentives, which captures direct incentives for OPSC to provide social support to patients (Wang et al., 2024; Yan and Tan, 2014) (as shown in Fig. 1).

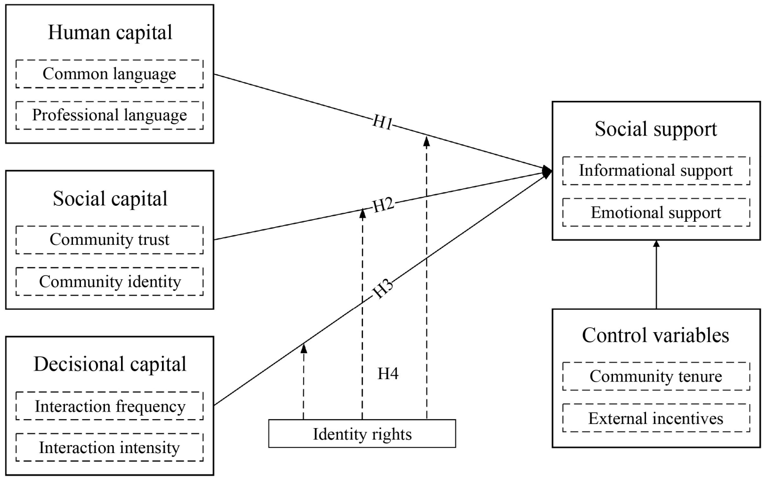

Fig. 1 Research model.

4 Research methodology

4.1 Data collection and processing

4.1.1 Data collection

One of the largest and most active online forums for diabetic patients in China serves as a platform where patients and their families exchange knowledge about diabetes, manage blood sugar control, and share personal experiences. The forum is divided into several modules, and our study focused on the most active module, dedicated to Type 2 diabetes, as the source of our sample data.

To collect the data, a Python script was used to regularly capture interaction history records and members' personal information from January 2018 through mid-December 2019. The interaction history records consist of post ID, post content, post user ID (the ID of the member who initiated the topic), post time (the timestamp of the post), reply ID (the ID of the member replying to a post), and reply content (the responses to the initial posts). The personal information gathered includes user ID, date of birth, gender, address, member rights, bonus points, registration date, email verification status, and space access. The resulting data set comprised 227,901 replies from 5,977 members. This comprehensive data set provides a robust foundation for analyzing member interactions, the sharing of social support, and the influence of professional capital on community engagement.

4.1.2 Data processing

During data collection and parsing, issues such as data loss, coding errors, and messy data can occur due to transmission errors or coding conflicts. To ensure data quality, a thorough data cleansing process was implemented, which involved the following steps:

(1) Decoding: The raw data collected by the Python script was decoded into readable text format.

(2) Excluding samples: We removed samples with missing values and excluded abnormal users, such as forum moderators and administrators, to maintain the integrity of the data set.

In alignment with our research objectives, the cleaned data was divided into three distinct subsets, as outlined in Table 3:

- Data set I was used to train automatic text classifiers.
- Data set II consists of a sample of 1,222 members, capturing users' communication records during the first three months of the study period.
- Data set III contains records of the users' social behavior during the subsequent three months.

The data sets were structured in chronological order to support the research design. To reduce potential endogeneity, we adopted a lagged variable structure by ensuring that all independent variables were derived from an earlier period than the dependent variables. Specifically, independent variables were extracted from Data set II (the earlier time period), while dependent variables were derived from Data set III (the later period). While this temporal design does not fully eliminate endogeneity, it helps mitigate concerns related to reverse causality and strengthens the internal consistency of the empirical model.

4.2 Text mining

4.2.1 Text classifier

In this study, an automatic text classifier was developed using machine learning to determine whether the interaction records indicate the provision of **informational support** or **emotional support**. The main workflow of the text classifier is illustrated in Fig. 2:

The detailed steps of the automatic text classifier are as follows:

Table 3 Description of the three Data sets

Data set	Purpose	Descriptions	Observation
I (2018.01–2018.12)	Train automatic text classifiers	From January to December 2018, this data set was sampled to train the automatic text classifier so that it could automatically identify whether the users' replies contained informational or emotional support.	159,145 (Sampled 7,000)
II (2019.03–2019.05)	Extract independent variables	From March through May 2019, independent variables (including professional capital related indicators) of 1,222 members who made replies during June through August 2019 were extracted.	25,215
III (2019.06–2019.08)	Extract dependent variables	The reply message data set from June through August 2019 identifies members' replies as informational support or emotional support, using the number of messages containing each type of support as the dependent variable.	19,433

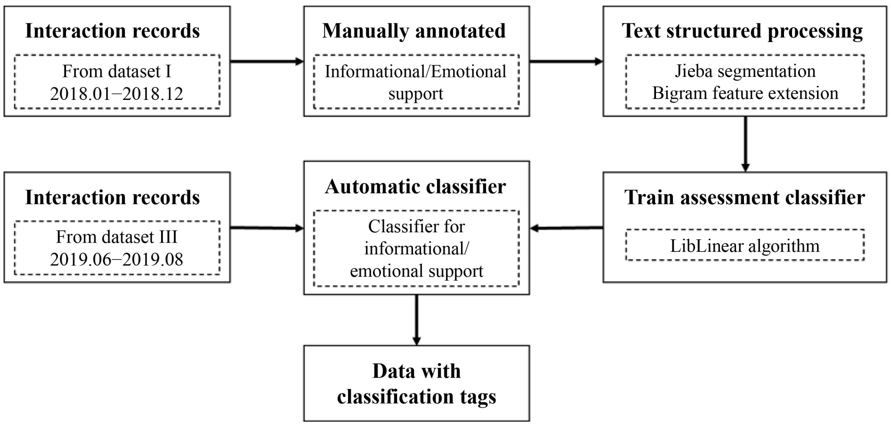

Fig. 2 Flow chart of text classifier.

Step 1: Manual Annotation. During the training process, 7,000 interaction records were randomly selected from Data set I (2018) and manually annotated according to two dimensions: informational support and emotional support. Each record was labeled with "1" for positive samples (i.e., records containing the specified type of support) and "0" for negative or other records.

● Text was considered to contain informational support if it provided knowledge that could reduce the recipient's uncertainty, such as health information, disease knowledge, treatment advice, or medication guidance.

● Text was considered to contain emotional support if it reflected emotional content, such as empathy, care, comfort, encouragement, or expressions of love.

To ensure consistency in judgment, the annotation was performed solely by the authors, which involved a significant workload (See Appendix A for the specific annotation process). Table 4 lists the text categories that contain informational or emotional support.

Step 2: Structured Text Processing. We used TextGrocery, a short-text classification tool based on the LibLinear algorithm and Jieba word segmentation, as our automatic text classifier. This tool is efficient, easy to use, and supports both Chinese and English corpora. TextGrocery offers a straightforward API, and its underlying principles are supported by solid experimental data (with no filtered words or parts of speech, and linear kernels).

To process short text automatically, we applied the Jieba word segmentation tool embedded in TextGrocery and utilized a feature construction algorithm based on epigrams to enable automatic feature extraction. To address the issue of imbalanced distribution of positive and negative samples in the training set, we increased the number of samples in the minor categories to match that of the major category (with ratios of 3:7 and 2:8 for informational and emotional support, respectively).

Step 3: Train and Assess the Classifier. We randomly selected 7,000 items from Data set I to train and test the text classifier. The classification model was built on the two dimensions of social support: informational support and emotional support.

To ensure robustness and generalizability, we adopted a Sliding Test Set Cross-Validation (k = 10) approach. Specifically, the data set was divided into 10 equal parts. In each of the 10 iterations, two consecutive parts were used as the test set, and the remaining eight parts served as the training set. This sliding structure ensured that each data point appeared in the test set exactly twice, enabling broader coverage and more reliable assessment across data subsets.

(1) The training set was input into the TextGrocery short-text classification algorithm, which is based on the support vector machine (SVM) model, to build the classifier.

(2) The test set was used to evaluate the trained classifier. The results showed that the classifier met the required

Table 4 Examples of texts containing informational support or emotional support

Classification dimensions	Training classes	Examples
Informational Support	Positive samples	"The side effects of that medicine are far greater than Acarbose, you'd better keep taking Acarbose as it is the first recommended medication according to the medication dictionary. Only if Acarbose is unable to control your disease, you have to change to another one." "The machine needs less blood and is relatively more accurate. However, its test strips only come in small batches, so it's more expensive."
	Negative sample	"You don't need to follow a cycle or frequency of insulin shots. I recommend taking them before a big meal."
Emotional Support	Positive samples	"Do not worry too much! You can pay more attention to the disease treatment, but anxiety is not good. No matter what, try to maintain a good state of mind! Some people who have no disease also have anxiety disorders, which I think more serious than our chronic diseases." "I really appreciate your cautious attitude."
	Negative sample	"You must try your best to keep it under control as your condition is not as good as it should be."

accuracy for identifying whether messages contained informational support or emotional support, with an average test accuracy of 89.7% for informational support and 94.1% for emotional support. The classifier's performance was stable across tests. Additionally, we assessed the effect of sample size on classifier performance. The learning curve, shown in Fig. 3, indicates that from 1,000 to 7,000 samples, the classifier's learning curve converged, suggesting that a sample size of 7,000 is sufficient for effective training.

Step 4: Automatic Classifier. we employed the trained classifier to automatically determine the type of social support—informational support or emotional support—present in the interaction records of Data set III (spanning from June 2019 through August 2019). The classifier, which was trained and tested using the annotated data from Data set I, was applied to the larger volume of interaction data in Data set III to classify each record based on the social support it provided.

By automating the classification process, we were able to efficiently analyze the nature of support exchanges across a substantial portion of the data set, allowing for in-depth insights into how members of the community shared informational and emotional support during this period. This automated classification is critical for scaling the analysis to cover extensive interaction records while maintaining a high level of accuracy and consistency.

4.2.2 Text similarity calculation: measuring common language in HCPC

In the human capital dimension (HCPC), common language refers to members' mastery of the community's specific language related to its core topics. This common language reflects the shared terminology, knowledge, and communication patterns that members use to discuss topics within the community. According to the literature, common language can be measured by assessing the similarity between a member's language in their interaction records and the overall thematic focus of the forum (Chang and Chuang, 2011; Chiu et al., 2006).

In this study, common language is operationalized as the degree to which a member's interaction aligns with the community's dominant topics, representing their ability to effectively share and exchange information. To quantify this, we adopted a natural language processing (NLP) method using Latent Dirichlet Allocation (LDA), a topic modeling technique, to identify key themes and calculate the similarity between a member's interaction-record language and the overall topic distribution of the forum (Wu, 2013). This measure reflects the extent to which members are proficient in the community's shared discourse, as outlined in the hypotheses.

The steps for calculating the similarity between the interaction-record language and the overall topic of the community are shown in Fig. 4 and the detailed steps are as follows:

Step 1: Jieba word segmentation. We used Jieba word segmentation, a tool for Chinese language processing, to break each text into individual words. This segmentation allows us to structure the text data for further analysis.

Step 2: Stopword elimination. After segmentation, we applied a stopword elimination process using a Chinese dictionary. This step filters out commonly used but semantically irrelevant words (e.g., conjunctions, prepositions) to focus on more meaningful terms.

Step 3: Word vector building using the BoW model. We employed the bag-of-words (BoW) model, which ignores word order and syntax but treats the text as a collection of individual words. Word vectors were constructed from the interaction texts in the OPSC forum from 2019 and from each member's summary reply text in Data set II.

Step 4: LDA model training. We applied the LDA topic modeling technique to train the topic distribution using interaction records from 2019. The model parameters were set as num_terms = 65447, num_topics = 10, decay = 0.5, and chunksize = 2000. LDA generated 10 core topics, such as:

Topic 1: Medication precautions for diabetic patients.
Topic 2: Daily management experiences with diabetes.
Topic 3: Diabetes onset and control strategies.
Topic 4: Diet and exercise routines.

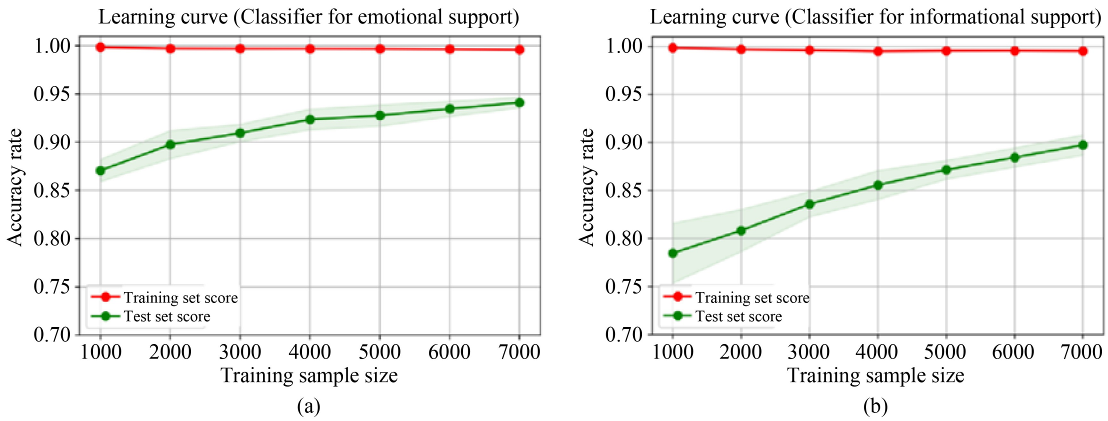

Fig. 3 Text classifier learning curves, classifier for (a) emotional support and (b) informational support.

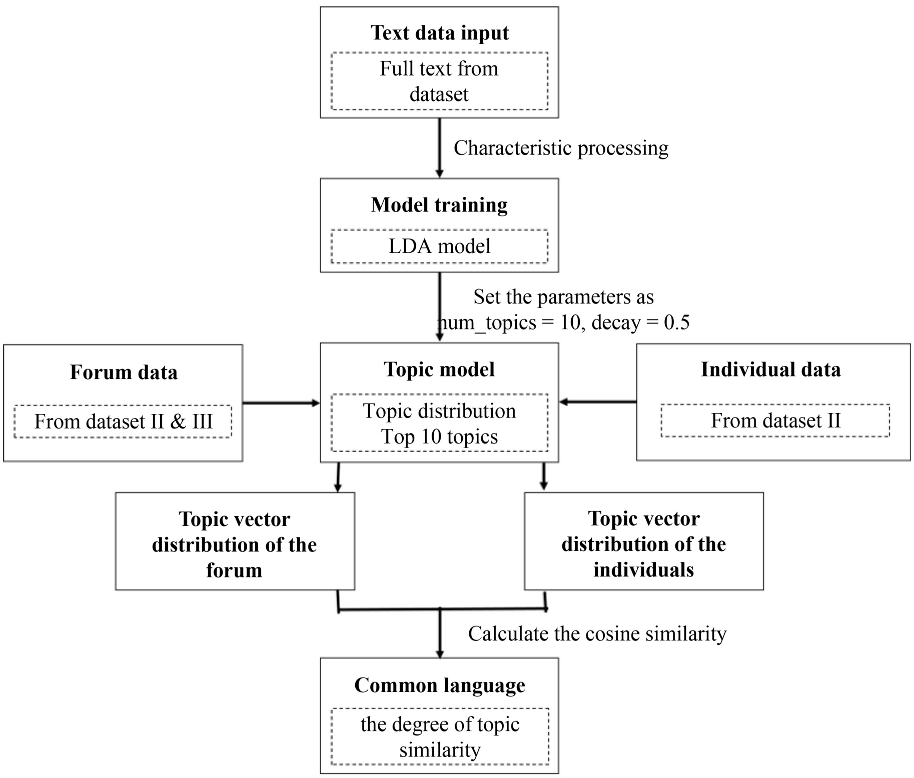

Fig. 4 Topic similarity calculated by LDA processing.

Topic 5: Blood glucose control techniques.
Topic 6: Hypoglycemia Management
Topic 7: Healthy Eating Tips
Topic 8: Physical Activity Tips
Topic 9: Coping with Stress
Topic 10: Health Management Technology

The keywords and weight distributions of the ten topics are detailed in Table 5.

Step 5. Topic distribution and similarity calculation. Using the trained LDA model, we calculated the topic distribution vectors at both the community level and the individual member level.

For the community-level distribution, we applied the LDA model to all replies posted within the community (Data set I). The model generated a topic distribution vector for each reply, which was then aggregated via element-wise summation and normalized to obtain a single vector representing the proportional presence of each topic in the community's overall discourse.

For the member-level distribution, we applied the same LDA model to each member's replies in Data set II. Each member's topic distribution vector was computed by aggregating their post-level topic distributions and normalizing the result to ensure comparability.

We then used cosine similarity to measure the degree of alignment between a member's language and the overall

Table 5 Keywords mined by LDA and weight distribution

Topics	Weight Distribution of Keywords
1	0.011*"study" + 0.010*"epilepsy" + 0.008*"diabetes" + 0.006*"indicate" + 0.006*"cholesterol" + 0.006*"handbook" + 0.006*"patient" + 0.005*"China" + 0.005*"vessel" + 0.005*"lesion"
2	0.038*"eat" + 0.014*"medicine" + 0.014*"doctor" + 0.009*"say" + 0.008*"feeling" + 0.006*"hurt" + 0.006*"weak" + 0.006*"try" + 0.006*"water" + 0.006*"winter"
3	0.031*"say" + 0.028*"diabetes" + 0.018*"doctor" + 0.015*"sugar" + 0.012*"complication" + 0.012*"do" + 0.010*"control" + 0.010*" month" + 0.009*"diagnosis" + 0.009*"year"
4	0.048*"blood glucose" + 0.037*"diet" + 0.026*"control" + 0.020*"excise" + 0.010*"treat" + 0.010*"body" + 0.009*"impact" + 0.008*" medicine" + 0.008*"take" + 0.007*" Keto"
5	0.035*"limosis" + 0.032*"blood glucose" + 0.026*"hour" + 0.024*"after the meal" + 0.018*"take" + 0.015*"high" + 0.014*"second meal" + 0.014*"test" + 0.013*"dimethyl" + 0.013*"saccharify"
6	0.035*"shaking" + 0.030*"dizziness" + 0.023*"sweating" + 0.021*"blur" + 0.020*"numbness" + 0.017*"heartbeat" + 0.015*"snack" + 0.013*"chocolate" + 0.012*"syrup" + 0.010*"emergency"
7	0.055*"fiber" + 0.048*"fruit" + 0.028*"nuts" + 0.025*"berries" + 0.022*"grains" + 0.020*"veggies" + 0.018*"oil" + 0.015*"fish" + 0.012*"balance" + 0.010*"snacks"
8	0.035*"walking" + 0.030*"yoga" + 0.028*"stretching" + 0.025*"steps" + 0.022*"aerobic" + 0.020*"swim" + 0.018*"movement" + 0.015*" fitness" + 0.012*"strength" + 0.010*"bands"
9	0.040*"breathing" + 0.035*"focus" + 0.030*"calm" + 0.028*"depress" + 0.025*"relaxation" + 0.022*"resilience" + 0.018*"therapy" + 0.015*"mindset" + 0.012*"breaks" + 0.010*"cry"
10	0.035*"devices" + 0.030*"apps" + 0.028*"tracking" + 0.025*"monitor" + 0.022*"data" + 0.020*"alerts" + 0.018*"wearable" + 0.015*" features" + 0.012*"updates" + 0.010*"sync"

community topics.

$$\text{Similarity}(\mu,\nu) = \cos(\theta) = \frac{\mu\cdot\nu}{\|\mu\|\,\|\nu\|},$$

where μ represents the topic distribution vector of member i ($\overrightarrow{\text{Member}_i}$), and ν represents the topic distribution vector of the community ($\overrightarrow{\text{Community}}$).

The similarity value ranges from 0 to 1:

● 0 means little to no alignment between the member's language and the community's topics.

● 1 means a high degree of alignment, reflecting strong mastery of the community's common language.

This measurement aligns with the common language concept outlined in the hypotheses, capturing how well a member's communication conforms to the community's topic-based language, which is a critical component of their human capital in the OPSC.

4.2.3 Matching the word and text: measuring professional knowledge in HCPC

In the human capital dimension (HCPC), professional knowledge represents a member's familiarity with medical concepts, treatments, and terminology within the context of the disease field addressed by the OPSC. To measure this dimension of professional knowledge, we applied a word matching sampling method to quantify the use of professional terminology in members' interaction records. The process was as follows:

Building a professional dictionary: We developed a comprehensive professional dictionary by merging the open-source Chinese medical dictionary from Tsinghua University with a Chinese diabetes health dictionary based on network data and medical expertise. This dictionary encompasses key medical terms, including disease names, treatments, medications, and other relevant healthcare-related terminology.

Text processing with Jieba segmentation: The text data from members' interactions was segmented using Jieba word segmentation to break the text into individual words. This segmentation enabled the structured processing of text data, turning the interaction records into word units for analysis.

Word matching with professional terms: The segmented words from each user's text were matched with the professional terms in the medical dictionary. This step identified whether the words used in the interaction records matched professional medical terms. By doing this, we could determine how frequently and broadly users incorporated professional language into their communication.

Quantifying the professional index: The professional index was calculated by two metrics:

● By Category: The number of distinct categories of professional medical terms used by the user (e.g., diseases, treatments, medications).

● By Frequency: The total number of times professional terms appeared in the user's messages.

The professional index serves as a quantitative measure of each member's professional knowledge in the forum, reflecting their command of relevant medical terminology. This dimension of professional knowledge is a critical aspect of the member's human capital (HCPC), indicating their expertise and understanding in the healthcare domain, particularly in diabetes management.

4.3 Variable definitions and descriptive analysis

4.3.1 Variable definitions

The definitions, operationalizations, and measurements of the key variables are shown in Table 6. According to our research model, the dependent variables are the provision of social support, which includes:

- *Informational_support*
- *Emotional_support*

The independent variable is professional capital, which consists of three dimensions:

DCPC (Decisional Capital): Measured by *interaction frequency* and *interaction intensity,* indicating the frequency and depth of a member's engagement within the community.

SCPC (Social Capital): Defined by two sub-dimensions:

- *Community_Trust*: Measured by the voluntary disclosure of personal information (e.g., age, gender, residence) in user profiles. Drawing on privacy literature, such disclosure, particularly when optional, is interpreted as a behavioral signal of trust in the community environment (Dinev and Hart, 2006; Ommen et al., 2011).
- *Community_Identity*: Represents the extent to which members identify with the community, driving their motivation to contribute to the collective well-being.

HCPC (Human Capital): Measured by:

- *Common_Language*: Mastery of the community's specific language, allowing effective communication within the group.
- *Professional_Knowledge*: The use and understanding of specialized medical terms, reflecting the member's expertise in healthcare and disease management.

To control for factors that might influence the provision of social support, we include two control variables:

- *External_Incentives*: This control variable captures the extrinsic motivation that drive members to provide social support. It reflects how external rewards or incen-

Table 6 Definitions, operationalizations, and measurements of the key variables

Variables	Definitions	Operationalizations	Measure
Dependent Variables			
Informational support (*Informational_Support*)	Support used for reducing uncertainty and promoting problem-solving, such as sharing health-related knowledge	Identified by text mining	The number of interaction records containing informational support posted by the members of the OPSC during the data collection period
Emotional support (*Emotional_Support)*	Support provided to restore emotional stability via sympathy and encouragement	Identified by text mining	The number of interaction records containing emotional support posted by the members of the OPSC during the data collection period
Independent Variables			
Interaction Frequency (*Interaction_Frequency*)	The diversity of information received by members and the degree of exposure to other members	Constructed by observation variables	The average number of interaction records generated on days that a member actively participates in the OPSC; this is calculated by the equation: $\text{Interaction\_Frequency} = \frac{\text{the total number of interaction records}}{\text{the member's active participation days}}$
Interaction Intensity (*Interaction_Intensity*)	The depth of information exchange between members	Constructed by observation variables	The average number of interaction records in which the member is participating by posting in the OPSC. This is calculated by the equation: $\text{Interaction\_Intensity} = \frac{\text{the total number of interaction records}}{\text{the member's posts}}$
Community Trust (*Community_Trust*)	the level of trust members have in the community, influencing their willingness to share and receive support	Calculated by observation variables	The degree of community trust is measured by the extent to which a member discloses personal information (age, gender, residence) in the OPSC. Each disclosure is assigned a value of 1, with the total trust score ranging from 0 to 3 based on the number of disclosures.
Community Identity (Community *_Identity)*	the extent to which members identify with the community, driving their motivation to contribute to the collective well-being	Calculated by observation variables	The number of two-way friends (users who have designated each other as friends) is used to measure the social identity of a member of the OPSC (Ellemers et al., 1999; Huang et al., 2019)
Professional Knowledge (*Professional_ Knowledge*)	The degree to which an OPSC member has acquired diabetes-related professional knowledge	Identified by the word segmentation method (Jieba word segmentation)	The number of professional medical vocabulary categories contained in the member's interaction history records
Common Language (*Common_Language*)	The degree of similarity between the topic contained in the member's interaction records and the overall posts of the OPSC	Identified by the LDA topic mining method	The similarity of the member's interaction records to the records of the OPSC overall. It is calculated by the equation: $\text{Similarity}(\mu,\nu)=\cos(\theta)=\frac{\mu\cdot\nu}{\lVert\mu\rVert\,\lVert\nu\rVert}$
Identity Rights (*Identity_Rights*)	The user's rights in the OPSC based on their participation history, which grants access to certain platform features	Calculated by observation variables	The degree of platform rights, quantified into a range of right numbers (1-12)
Control Variables			
External Incentives (*External_Incentives*)	The OPSC's direct reward mechanism for patients to provide social support, indicating extrinsic motivation	Calculated by observation variables	The total number of gold coins awarded by the OPSC for signing in, adding tags to posts, posting, and replying
Community Tenure (*Community_Tenure*)	The cumulative length of a patient's use of the OPSC, reflecting their experience and ability to provide social support	Calculated by observation variables	The total number of months from the date of initial registration to August 2019 (data collection deadline)

tives influence the willingness of patients to engage in supportive behaviors within the community.

- *Community_Tenure*: This reflects the duration of participation in the community. It indicates the member's experience and familiarity with the community, which can enhance their ability to provide social support. A longer tenure is associated with greater integration and understanding of the community's norms and values, thus facilitating more effective support provision.

4.3.2 Descriptive statistics

The descriptive statistics for each variable are shown in Table 7. As mentioned above, the sample size of valid OPSC members is 1,222. In terms of interaction frequency and intensity, a member participated in an average of 1.24 posts per day and responded 1.71 times per post. Moreover, an average member voluntarily disclosed 0.9 pieces of private information and had 3.31 two-way friends. Although these statistics indicate that the focal OPSC has a relatively low level of SCPC overall, there are still members with high trust and high social identity (with maximum values of 3 and 466, respectively). Furthermore, members used an average of 4.46 professional words, and the similarity of their text with community topics was 0.6. The average number of informational support interactions provided by each member was 10.68, while the number of emotional support interactions was 2.70. Additionally, the maximum and average values of the two dimensions of support show a significant difference, and the data exhibit a skewed distribution.

The correlation analysis in Table 8 shows that the correlation coefficients between the dependent variables (Informational Support and Emotional Support) and other independent variables are all below 0.6, indicating no high correlation between them. Similarly, the correlation coefficients among explanatory variables are below 0.5, suggesting no strong collinearity between independent variables.

The variance inflation factor (VIF) for each independent variable is below 10, confirming that there is no multicollinearity issue in the model, and each variable provides a unique contribution to the analysis.

This analysis suggests that each dimension of profes-

Table 7 Descriptive statistics

Variables	Samples	Mean	Standard Deviation	Minimum	Maximum
Interaction_frequency	1222	1.237	0.649	0.250	8.104
Interaction_intensity	1222	1.706	1.676	1.000	23.000
Community_trust	1222	0.962	1.142	0.000	3.000
Community _identity	1222	3.312	19.395	0.000	466.000
Professional_knowledge	1222	4.461	4.976	0.000	33.000
Common_language	1222	0.608	0.168	0.000	0.919
Identity Rights	1222	3.863	2.704	0.000	12.000
Community_Tenure	1222	22.986	33.270	0.000	167.100
External_Incentives	1222	764.471	4200.483	0.000	96586.000
Informational_support	1222	10.677	49.490	0.000	1035.000
Emotional_support	1222	2.696	10.229	0.000	176.000

Table 8 Correlation analysis between variables (Pearson correlation coefficient)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	VIF
(1) *Interaction_frequency*	1.000											1.084
(2) *Interaction_intensity*	−0.121	1.000										1.055
(3) *Community_trust*	0.059	0.014	1.000									1.080
(4) *Community_identity*	0.042	0.008	0.107	1.000								1.180
(5) *Professional_knowledge*	0.125	0.186	0.002	0.036	1.000							1.160
(6) *Common_language*	0.169	0.164	0.012	−0.025	0.476	1.000						1.180
(7) *Identity Rights*	0.093	−0.010	0.348	0.340	0.020	0.059	1.000					1.861
(8) *Community Tenure*	−0.061	−0.013	0.259	0.303	−0.009	−0.047	0.573	1.000				1.587
(9) *External Incentives*	−0.019	0.011	0.150	0.179	0.014	−0.042	0.395	0.176	1.000			1.269
(10) *Informational_support*	0.457	0.064	0.086	0.191	0.154	0.107	0.210	0.007	0.070	1.000		–
(11) *Emotional_support*	0.415	0.123	0.061	0.204	0.115	0.143	0.234	0.004	0.075	0.769	1.000	–

sional capital (DCPC, SCPC, and HCPC) represents distinct aspects of members' engagement and contributions to the OPSC, with no significant overlap, allowing us to rule out collinearity concerns.

4.4 Regression analytics

4.4.1 The impact of SCPC on social support

Based on the research hypotheses we developed, we establish the following multiple linear regression model. The dependent variables are informational support and emotional support, and the independent variables include interaction frequency, interaction intensity, community trust, community identity, professional knowledge, common language, identity rights, community tenure, external incentives.

Linear regression model with informational support as the dependent variable:

$$\begin{aligned} Informational\_Support_i &= \beta_0+\beta_1 Interaction\_Frequency_i+\beta_2 Interaction\_Intensity_i+\beta_3 Community\_Trust_i+ \\ &\beta_4 Community\_Identity_i+\beta_5 Professional\_Knowledge_i+\beta_6 Common\_Language_i+\beta_7 Identity\_Rights_i+ \\ &\beta_8 External\_Incentives_i+\beta_9 Community\_Tenure_i+\varepsilon_i, \end{aligned} \tag{1}$$

Linear regression model with emotional support as the dependent variable:

$$\begin{aligned} Emotional\_Support_i &= \beta_0+\beta_1 Interaction\_Frequency_i+\beta_2 Interaction\_Intensity_i+\beta_3 Community\_Trust_i+ \\ &\beta_4 Community\_Identity_i+\beta_5 Professional\_Language_i+\beta_6 Common\_Language_i+\beta_7 Identity\_Rights_i+ \\ &\beta_8 External\_Incentives_i+\beta_9 Community\_Tenure_i+\varepsilon_i, \end{aligned} \tag{2}$$

where β_i, i = 1, 2,…, 9 are estimated parameters, i refers to an individual patient, and ε_i is the error term.

To deal with the skew distribution of dependent variables, we employ the logarithm of dependent variables. The coefficients of the two regression models are calculated by least square estimation. To compare the coefficients in the two regression models, we perform a regression with the standard coefficients as results. The regression coefficients and statistical significance of variables in the model are shown in Table 9 and Fig. 5.

The regression results of Model 1 (informational support as the dependent variable) indicate that: (1) For DCPC, interaction frequency has a significant positive impact on the provision of informational support (β = 0.284, $P < 0.001$); interaction intensity also has a significant positive impact on the provision of informational support (β = 0.139, P < 0.001). Thus, H1a is supported. (2) For SCPC, community trust has no significant effect on the

Table 9 Results of the impact of SCPC on social support

DV	Ln(*Informational_Support*) (Model 1)		Ln(*Emotional_Support*) (Model 2)	
IV	Std Coefficients	p-value	Std Coefficients	p-value
Constant	0.000	1.000	0.000	1.000
(DCPC)				
Interaction_frequency	0.284***	0.000	0.319***	0.000
Interaction_intensity	0.139***	0.000	0.153***	0.000
(SCPC)				
Community_trust	−0.043	0.062	−0.024	0.338
Community_identity	0.050*	0.031	0.070**	0.006
(HCPC)				
Professional_knowledge	0.303***	0.000	0.094***	0.000
Common_language	0.147***	0.000	0.169***	0.000
Identity_rights	0.375***	0.000	0.357***	0.000
(Control Variables)				
Community_tenure	−0.135***	0.000	−0.197***	0.000
External_incentives	−0.031	0.187	0.025	0.319
Adjusted R_square	0.437		0.343	

Note: *** represents p < 0.001, ** represents p < 0.01, * represents p < 0.05

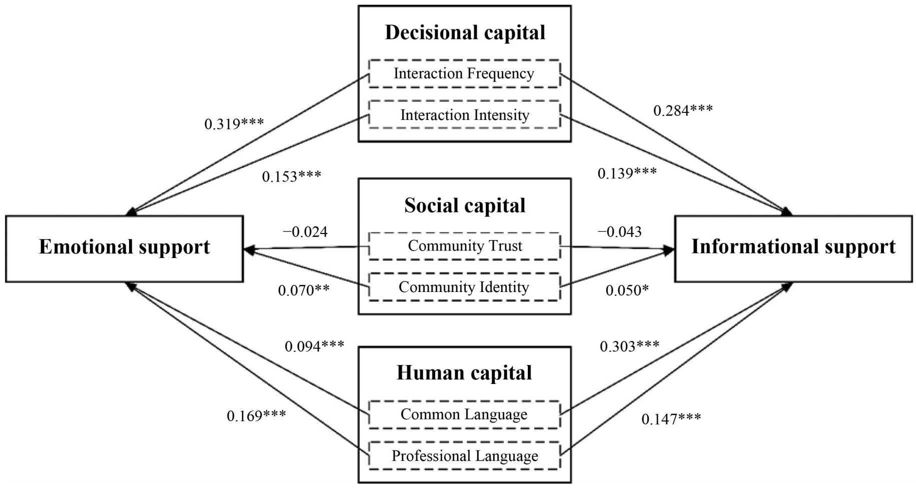

Fig. 5 Regression results.

provision of informational support (β = –0.043, P > 0.05); community identity has a significant positive impact on the provision of informational support (β = 0.050, P < 0.05). Thus, H2b is partially supported. (3) For HCPC, professional knowledge has a positive impact on the provision of informational support (β = 0.863, P < 0.001), and common language has a positive impact on the provision of informational support (β = 0.147, P < 0.001). Thus, H3a is supported.

Model 2 is a regression model for emotional support, and it explains 34.3% of the variation of the dependent variable. According to the regression results of Model 2, we see that: (1) For DCPC, interaction frequency has a significant positive impact on the provision of emotional support (β = 0.319, P < 0.001); interaction intensity has a significant positive impact on the provision of emotional support (β = 0.153, P < 0.001). Thus, H1b is supported. (2) For SCPC, trust has no significant effect on the provision of emotional support (β = –0.024, P > 0.05); community identity has a significant positive impact on the provision of emotional support (β = 0.070, P < 0.05). Thus, H2b is partially supported. (3) For HCPC, professional knowledge has a positive impact on the provision of emotional support (β = 0.094, P < 0.001), and common language also has a positive impact on the provision of emotional support (β = 0.169, P < 0.001). Thus, H3b is supported.

4.4.2 The moderating effect of identity rights

To test the moderating effect of identity rights on the impact of professional capital on social support, we add the interaction variables of explanatory variables and identity rights into the preliminary regression model in steps. The regression analysis results are shown in Table 10 and Table 11.

Compared with the results of Model 1 shown in Table 9, Models 3 and 4 have better explanatory ability (the adjusted R-squares are improved). The results show that identity rights have a significant positive moderating effect on the relationship between DCPC (interaction frequency and interaction intensity) and informational support (β = 0.550, P < 0.001 and β = 0.139, P < 0.01, respectively). Meanwhile, Models 5 and 6 show decreased explanatory ability (the adjusted R-squares decrease). The results show that identity rights have no significant moderating effect on the relationship between SCPC (community trust and community identity) and informational support (β = 0.550, P > 0.05 and β = 0.139, P > 0.05, respectively). For the moderating effect on the relationship between HCPC (professional knowledge and common language) and informational support, the results show that identity rights have a significant positive moderating effect (β = 0.256, P < 0.001 and β = 0.351, P < 0.001).

Compared with the results of Model 2 shown in Table 9, Models 9 and 10 show improved explanatory ability (the adjusted R-squares are improved). The results show that identity rights have a significant positive moderating effect on the relationship between interaction frequency and emotional support (β = 0.583, P < 0.001), while identity rights have no significant effect on the relationship between interaction intensity and emotional support (β = 0.079, P > 0.05). Meanwhile, the explanatory ability of Models 11 and 12 is not improved. The results show that identity rights have no significant moderating effect on the relationship between trust and emotional support (β = −0.083, P > 0.05); identity rights do not have a significant moderating effect on the relationship between interaction intensity and emotional support (β = −0.086, P > 0.05). For the relationship between HCPC and social support, the results show that identity rights have a significant positive moderating effect for professional knowledge and common language (β = 0.209, P <

Table 10 Regression results with the moderating effect (informational support)

Independent Variables	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	0.000	0.000	0.000	0.000	0.000	0.000
(DCPC)						
Interaction_frequency	−0.034	0.281***	0.284***	0.284***	0.278***	0.279***
Interaction_intensity	0.133***	0.034	0.140***	0.139***	0.147***	0.144***
(SCPC)						
Community_trust	−0.049**	−0.043	−0.053	−0.043	−0.040	−0.038
Community _identity	0.019	0.0479*	0.050*	0.068	0.035	0.051*
(HCPC)						
Professional_knowledge	0.305***	0.306***	0.303***	0.303***	0.113**	0.305***
Common_language	0.142***	0.154***	0.148***	0.148***	0.158***	0.044
Identity_rights	−0.009	0.311***	0.370***	0.375***	0.272***	0.086
(Control Variables)						
Community_tenure	−0.104***	−0.137***	−0.136***	−0.136***	−0.141***	−0.129***
External_incentives	−0.018	−0.037	−0.033	−0.031	−0.043	−0.023
(Moderating Effect)						
Identity_rights Interaction_frequency*	0.550***					
Identity_rights Interaction_intensity*		0.139**				
Identity_rights Community_trust*			0.014			
Identity_rights Community _identity*				−0.018		
Identity_rights Professional_knowledge*					0.256***	
Identity_rights Common_language*						0.315***
Adjusted R_square	0.472	0.440	0.436	0.436	0.453	0.443

Note: *** represents $p < 0.001$, ** represents $p < 0.01$, * represents $p < 0.05$

0.001 and $\beta = 0.462$, $P < 0.001$, respectively).

4.4.3 Robustness tests

To ensure the reliability of our statistical significance calculations, we conduct robustness testing on our model, employing four methods with seven robustness analyses. At the variable level, we alter the measurements of the dependent and independent variables and then carry out the regression analysis again. First, considering the possibility that the amount of social support contained in the interaction records with different word counts may indicate different levels of support, we use the textual length of interaction records with informational and emotional support to measure the strength of social support (as our dependent variable). Second, in order to avoid the representation bias in model construction variables obtained from empirically collected data, we use similar data with different statistical dimensions (e.g., average number vs. total amount, active participation days vs. data collection period) and different measurement methods (e.g., crawled numbered data vs. text mining data) to create alternative calculations of professional capital (i.e., DCPC, SCPC, HCPC). Third, we introduced MC-BERT, a large language model pretrained on Chinese medical texts, as an alternative method for measuring Common Language in HCPC. Fourth, we applied Negative Binomial regression as a robustness check, which introduces an additional dispersion parameter, allowing it to handle over dispersed count data more effectively. Finally, to examine the different moderating effects of identity rights on professional capital and social support, we select samples of low-right and high-right members using a sample grouping method, then conduct regression analysis to observe whether the conclusions obtained are similar to our original conclusions. The results almost totally confirm our previous findings, with details provided below.

Robustness tests with alternative measurements of dependent variables. To test the robustness of the research model at the variable level, considering the different measurement methods of independent and dependent variables, we replace the value with other indicators. In the main regression model, we use the number of replied posts containing informational support or emotional support to measure social support. Considering that the amount of social support contained in the replied posts of different lengths may be different, we redefine the informational support variable as the textual length of

Table 11 Regression results with the moderating effect (emotional support)

Independent variables	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Constant	0.000	0.000	0.000	0.000	0.000	0.000
(DCPC)						
Interaction_frequency	−0.018	0.317***	0.320***	0.319***	0.314***	0.311***
Interaction_intensity	0.145***	0.093*	0.152***	0.152***	0.158***	0.159***
(SCPC)						
Community_trust	−0.0298	−0.024	0.031	−0.0242	−0.021	−0.016
Community _identity	0.037	0.068**	0.074**	0.1556	0.058*	0.072**
(HCPC)						
Professional_knowledge	0.097***	0.096***	0.094***	0.094***	−0.0609	0.0974***
Common_language	0.163***	0.172***	0.167***	0.170***	0.178***	0.018
Identity_rights						
(Control Variables)	−0.051	0.320***	0.387***	0.355***	0.274***	−0.0675
Community_tenure	−0.164***	−0.198***	−0.196***	−0.199***	−0.202***	−0.188***
External_incentives	0.040	0.0219	0.034	0.0271	0.016	0.038
(Moderating Effect)						
Identity_rights Interaction_frequency*	0.583***					
Identity_rights Interaction_intensity*		0.079				
Identity_rights Community_trust*			−0.083			
Identity_rights Community _identity*				−0.086		
Identity_rights Professional_knowledge*					0.209***	
Identity_rights Common_language*						0.462***
Adjusted R_square	0.382	0.344	0.344	0.343	0.354	0.356

Note: *** represents $p < 0.001$, ** represents $p < 0.01$, * represents $p < 0.05$.

the records that contain informational support and posts by the member in the OPSC during that period. The emotional support variable is redefined as the textual length of the records that contain emotional support and posts by the member in the OPSC during that period. Then we carry out the regression analysis again.

The results of the new regression analysis are shown in Table 12. They show that DCPC (interaction frequency, interaction intensity) and HCPC (professional knowledge, common language) have significant positive effects on the provision of informational support and emotional support, while SCPC (community trust, community identity) has no significant impact on the provision of social support. This conclusion is similar to our previous results, indicating that the regression model results are robust.

Robustness Tests with Alternative Measurements of DCPC. For the measurement of DCPC in our main regression model, we measure interaction frequency using the average number of posts the target member participates in during an active day. To measure interaction frequency in our robustness tests, we use the total frequency of the member's login behaviors in the observation period.

$$Interaction_{F}requency = \frac{\text{member's login days}}{\text{observation period}}.$$

For interaction intensity, the main model uses the average number of interaction records replied to by the member under participating posts. We now define interaction intensity as the average number of records replied to by the member during their active days.

$$Interaction\_Intensity = \frac{\text{total number of interaction records}}{\text{observation period}}$$

The results of the regression are shown in Table 13 below. Except for the fact that the influence of professional knowledge on emotional support is no longer significant, the results of this regression are similar to those in the main model.

Robustness tests with alternative measurements of SCPC. In our main regression model, the quantitative value of the degree of disclosure of personal information (age, gender, place of residence) of the OPSC member (0-3) is used to measure community trust (one dimension of social capital). To test the reliability of the measurement, we use the member's mailbox authentication status in the OPSC to measure their degree of trust in the community. We choose this factor because it has been

Table 12 Regression results (robustness tests by dependent variables)

DV	ln(*Informational_Support*))		ln(*Emotional_Support*)	
IV	Std coefficients	*p*-value	Std coefficients	*p*-value
Constant	0.000	1.000	0.000	1.000
(DCPC)				
Interaction_frequency	0.187***	0.000	0.252***	0.000
Interaction_intensity	0.135***	0.000	0.156***	0.000
(SCPC)				
Community_trust	−0.023	0.336	−0.011	0.683
Community _identity	0.029	0.214	0.043	0.097
(HCPC)				
Professional_knowledge	0.374***	0.000	0.129***	0.000
Common_language	0.193***	0.000	0.193***	0.000
Identity_rights	0.273***	0.000	0.320***	0.000
(Control Variables)				
Community_tenure	−0.087***	0.002	−0.178***	0.000
External_incentives	−0.036	0.131	0.013	0.627
Adjusted R-square	0.420		0.303	

Note: *** represents $p < 0.001$, ** represents $p < 0.01$, * represents $p < 0.05$.

Table 13 Regression results (robustness tests by DCPC)

DV	ln(*Informational_Support*))		ln(*Emotional_Support*)	
IV	Std coefficients	*p*-value	Std coefficients	*p*-value
Constant	0.000	1.000	0.000	1.000
(DCPC)				
Interaction_frequency	0.638***	0.000	0.650***	0.000
Interaction_intensity	0.136**	0.003	0.182***	0.000
(SCPC)				
Community_trust	−0.011	0.484	0.009	0.637
Community _identity	−0.023	0.157	−0.007	0.723
(HCPC)				
Professional_knowledge	0.181***	0.000	−0.033	0.101
Common_language	0.088***	0.000	0.106***	0.000
Identity_rights	0.138***	0.000	0.115***	0.000
(Control Variables)				
Community_tenure	−0.013	0.508	−0.070**	0.001
External_incentives	−0.018	0.285	0.039*	0.036
Adjusted R-square	0.722		0.649	

Note: *** represents $p < 0.001$, ** represents $p < 0.01$, * represents $p < 0.05$.

proven that users' authentication behavior (e.g., verifying their email, telephone number, or identification number) is related to community trust (Liu et al., 2005).

At the same time, we reconsider the measurement of community identity. Another potential way of evaluating community identity is through the preference of members for the group (Ellemers et al., 1999). According to a previously mentioned study (Cassell and Tversky, 2005), the frequency of using internal-group words (e.g., we, our, us, sugar friends, etc.) reflects the individual's preference for the organization's community identity. Therefore, we take as our alternative measurement the number of times that members use internal group pronouns.

The results of the regression analysis are shown in

Table 14 Regression results (robustness tests by SCPC)

DV	ln(*Informational_Support*)		ln(*Emotional_Support*)	
IV	Std coefficients	p-value	Std coefficients	p-value
Constant	0.000	1.000	0.000	1.000
(DCPC)				
Interaction_frequency	0.276***	0.000	0.313***	0.000
Interaction_intensity	0.132**	0.003	0.146***	0.000
(SCPC)				
Community_trust	0.062**	0.006	0.040	0.1
Community _identity	0.043 +	0.054	0.051*	0.034
(HCPC)				
Professional_knowledge	0.294***	0.000	0.086**	0.001
Common_language	0.136***	0.000	0.159***	0
Identity_rights	0.382***	0	0.371***	0
(Control Variables)				
Community_tenure	−0.129	0	−0.188***	0
External_incentives	−0.033	0.163	0.027	0.291
Adjusted R-square	0.438		0.343	

Note: *** represents $p < 0.001$, ** represents $p < 0.01$, * represents $p < 0.05$, + represents $p < 0.1$.

Table 14. The conclusion is consistent with the results of the previous analysis except for the fact that the effect of community trust on informational support becomes significant, indicating that the regression results in the main paper are robust.

Robustness Tests with Alternative Measurements of HCPC. In the main model, natural language processing is employed to mine and calculate the text of members' posts and replies. Due to the limitations of the LDA model in solving the topic discovery problem in short text, the vector space model based on TF-IDF is also commonly used in text similarity calculation. Therefore, as an alternative to using the similarity between members and forum topics (LDA model) to measure common language, we use the prototype language similarity calculation method to calculate the cosine similarity between the interaction records of the member (expressed as TF-IDF weighted eigenvectors) and the community forum prototype messages (the average value of all message vectors in the OPSC). At the same time, we replace professional knowledge as a measurement factor by the total number of professional words used by the member.

The results of the regression analysis are shown in Table 15. The conclusion is consistent with the results in the main paper, indicating that the paper's regression results are robust.

Robustness Tests with Alternative Measurement of Common Language in HCPC. To evaluate the robustness of our research model, we employed an alternative measurement of the common language variable. Previously, common language was quantified using Latent Dirichlet Allocation (LDA), a widely-used topic modeling technique. LDA calculates the similarity between a member's interaction records and the community's overall thematic focus by generating and comparing topic distributions. While effective in capturing thematic alignment, LDA's reliance on predefined topics may limit its ability to represent nuanced semantic relationships within the text comprehensively.

To address this limitation, we introduced MC-BERT, a large language model pretrained on Chinese medical texts, as an alternative method for measuring Common Language (Zhang et al., 2020a). Unlike LDA, which focuses on word co-occurrence patterns, MC-BERT generates contextualized semantic embeddings that capture deeper linguistic and contextual relationships. By leveraging MC-BERT, we generated semantic embeddings for both the member texts and the community text, then calculated the cosine similarity between these embeddings to measure their alignment. This similarity score served as a quantitative representation of a member's proficiency in the shared language of the community.

The results in Table 16 align with those from the LDA-based measurement. However, the effect of professional knowledge on emotional support is no longer significant. Aside from this, the findings are consistent with the main model.

Robustness Tests with Negative binomial regressions. To test the robustness of our research model, we initially employed Poisson regression, which is a standard approach for modeling count data. However, we found that the variances of the dependent variables were signifi-

Table 15 Regression results (robustness tests by HCPC)

DV	ln(*Informational_Support*)		ln(*Emotional_Support*)	
IV	Std Coefficients	p-value	Std Coefficients	p-value
Constant	0.000	1.000	0.000	1.000
(DCPC)				
Interaction_frequency	0.116***	0.000	0.170***	0.000
Interaction_intensity	0.062**	0.003	0.085***	0.000
(SCPC)				
Community_trust	−0.044*	0.039	−0.025	0.271
Community _identity	−0.014	0.504	0.002	0.944
(HCPC)				
Professional_knowledge	0.417***	0.000	0.378***	0.000
Common_language	0.323***	0.000	0.175***	0.000
Identity_rights	0.315***	0.000	0.317***	0.000
(Control Variables)				
Community_tenure	−0.069**	0.006	−0.151***	0.000
External_incentives	−0.061	0.005	−0.009	0.707
Adjusted R-square	0.529		0.435	

Note: *** represents $p < 0.001$, ** represents $p < 0.01$, * represents $p < 0.05$, + represents $p < 0.1$

Table 16 Regression results (robustness tests alternative measurement of common language in HCPC)

DV	ln(*Informational_Support*)		ln(*Emotional_Support*)	
IV	Std Coefficients	*p*-value	Std Coefficients	*p*-value
Constant	−1.822***	0.000	−1.892***	0.000
(DCPC)				
Interaction_frequency	0.545***	0.000	0.457***	0.000
Interaction_intensity	0.093**	0.002	0.099***	0.000
(SCPC)				
Community_trust	−0.022	0.578	−0.015	0.631
Community_identity	0.003	0.074	0.003*	0.038
(HCPC)				
Professional_knowledge	0.074***	0.000	0.014	0.076
Common_language	1.994***	0.000	1.882***	0.000
Identity_rights	0.181***	0.000	0.143***	0.000
(Control Variables)				
Community_tenure	−0.005**	0.005	−0.005***	0.000
External_incentives	0.000	0.399	0.000	0.366
Adjusted R-square	0.366		0.350	

Note: *** represents $p < 0.001$, ** represents $p < 0.01$, * represents $p < 0.05$.

cantly larger than their mean, indicating overdispersion. This violates the key assumption of Poisson regression, which requires the mean and variance of the dependent variable to be equal.

To address this issue, we applied Negative Binomial regression as a robustness check. Negative Binomial regression introduces an additional dispersion parameter, allowing it to handle over dispersed count data more effectively. The results of the Negative Binomial regression are presented in Table 17, showing the coefficients of the explanatory variables. Additionally, the Incident Rate Ratios (IRRs) derived from the Negative Binomial model are shown in Table 18 for better interpretability. Both tables demonstrate consistent findings: DCPC

Table 17 Regression results (robustness tests by negative binomial regressions)

DV	*Informational_Support*		*Emotional_Support*	
IV	Std coefficients	*p*-value	Std coefficients	p-value
Constant	−2.909***	0.000	−5.022***	0.000
(DCPC)				
Interaction_frequency	0.970***	0.000	0.880***	0.000
Interaction_intensity	0.269***	0.000	0.253***	0.000
(SCPC)				
Community_trust	−0.060	0.255	−0.083	0.159
Community_identity	0.002	0.071	0.003	0.466
(HCPC)				
Professional_knowledge	0.090***	0.000	0.035*	0.033
Common_language	2.313***	0.000	4.048***	0.000
Identity_rights	0.259***	0.000	0.297***	0.000
(Control Variables)				
Community_tenure	−0.005*	0.012	−0.006*	0.027
External_incentives	−0.001	0.514	0.001	0.906
α	1.475, 95%CI: [1.303; 1.668]		1.684, 95%CI: [1.410; 2.010]	

Note: *** represents p<0.001, ** represents p<0.01, * represents p<0.05.

Table 18 Regression results (robustness tests by negative binomial regressions)

DV	*Informational_Support*		*Emotional_Support*	
IV	IRR	*p*-value	IRR	*p*-value
Constant	0.055***	0.000	0.007***	0.000
(DCPC)				
Interaction_frequency	2.637***	0.000	2.411***	0.000
Interaction_intensity	1.309***	0.000	1.288***	0.000
(SCPC)				
Community_trust	0.941	0.255	0.920	0.159
Community_identity	1.002	0.071	1.003	0.466
(HCPC)				
Professional_knowledge	1.094***	0.000	1.036*	0.033
Common_language	10.106***	0.000	57.265***	0.000
Identity_rights	1.295***	0.000	1.346***	0.000
(Control Variables)				
Community_tenure	0.995*	0.012	0.994*	0.027
External_incentives	1.000	0.514	1.000	0.906
α	1.475, 95%CI: [1.303; 1.668]		1.684, 95%CI: [1.410; 2.010]	

Note: *** represents $p < 0.001$, ** represents $p < 0.01$, * represents $p < 0.05$.

(interaction frequency, interaction intensity) and HCPC (professional knowledge, common language, and identity rights) have significant positive effects on the provision of informational and emotional support, while SCPC (community trust, community identity) remains insignificant. These results confirm the robustness of our research model and findings.

Robustness tests with subgroup regression. To test the moderating effect of identity rights on professional capital and social support, we use the sample grouping method to select a sample of low-right and high-right members, then conduct regression analysis to observe whether similar conclusions could be obtained. Considering that the difference of the distribution frequency of different ranks is too big, the samples with identity rights values of 1 and 2 are classified as the low identity rights group, and the samples with identity rights values greater than or equal to 7 are classified as the high identity rights group. The regression analysis results of each group are shown in Table 19.

From Table 19, which compares the regression results of each subgroup where the dependent variable is informational support, we see that the interaction frequency of the high-right group has a stronger effect on providing informational support than that of the low-right group (low: $\beta = 0.079$, $p < 0.05$; high: $\beta = 0.475$, $p < 0.001$). Interaction intensity of high-right members has a stronger effect on providing informational support than that of low-right members (low: $\beta = 0.118$, $p < 0.01$; high: $\beta = 0.198$, $p < 0.001$). These results show that the impact of the professional knowledge of high-right group members on informational support is stronger than that of low-right group members (low: $\beta = 0.341$, $p < 0.001$; high: $\beta = 0.354$, $p < 0.001$). The impact of common language on high-right members' informational support provision is lower than that the impact for low-right members (low: $\beta = 0.205$, $p < 0.001$; high: $\beta = 0.092$, $P < 0.1$).

Comparing the regression results of each subgroup where the dependent variable is emotional support, we see that the impact of the interaction frequency on informational support provision of the high-right member group is stronger than it is in the low-right group (low: $\beta = 0.167$, $p < 0.001$; high: $\beta = 0.510$, $p < 0.001$). Interaction intensity of the high-right group has a stronger effect on informational support provision than it does for the low-right group (low: $\beta = 0.154$, $p < 0.001$; high: $\beta = 0.157$, $p < 0.01$). The impact of professional knowledge of the high-right group on informational support provision is stronger than that of the low-right group (low: $\beta = 0.038$, $P > 0.1$; high: $\beta = 0.116$, $P < 0.05$). The impact of common language on high-right members' informational support provision is lower than that of the low-right group (low: $\beta = 0.188$, $p < 0.001$; high: $\beta = 0.153$, $p < 0.01$). Except for the moderating effect of identity rights on common language, which differs from our previous results, the conclusions are similar to the results of the main analysis. This consistency demonstrates that the moderating effect of identity rights on DCPC and HCPC obtained in the informational support and emotional support models in the main paper is credible.

5 Discussion

5.1 Key findings

This study examines the comprehensive influence of professional capital (conceptualized using a three-dimensional framework: human capital, social capital, and decisional capital) on OPSC members' provision of informational and emotional support. By integrating econometric modeling and text mining techniques, we were able to provide a more nuanced and accurate assessment of the effects of professional capital on social support behaviors

Table 19 Regression results (robustness tests by sub-group regression)

DV/IV	ln(*Informational_Support*))		ln(*Emotional_Support*)	
Sample Groups	Low group	High group	Low group	High group
Constant	0.000	0.000	0.000	0.000
(DCPC)				
Interaction_frequency	0.079*	0.475***	0.167***	0.510***
Interaction_intensity	0.118**	0.198***	0.154***	0.157**
(SCPC)				
Community_trust	−0.059	−0.016	0.034	−0.081
Community_identity	0.061	0.066	0.029	0.113+
(HCPC)				
Professional_knowledge	0.341***	0.354***	0.038	0.116*
Common_language	0.205***	0.092+	0.188***	0.153**
Identity_rights	0.019	0.095	0.033	0.069
(Control Variables)				
Community_tenure	0.036	−0.044	−0.068	−0.102+
External_incentives	0.037	0.006	−0.072+	0.122*
Sample Size	533	237	533	237
Adjusted R-square	0.278	0.507	0.106	0.431

Note: *** represents $p < 0.001$, ** represents $p < 0.01$, * represents $p < 0.05$, + represents $p < 0.1$.

within OPSCs.

Our key findings highlight the holistic nature of professional capital, emphasizing how its three dimensions collectively contribute to the provision of social support:

Decisional Capital (DCPC): Both interaction frequency and interaction intensity have significant positive effects on the provision of informational and emotional support (Models 1 and 2). These results confirm that members' decision-making abilities, built through frequent and deep interactions, are critical to social support provision. This reinforces the notion that DCPC plays a pivotal role in facilitating support, as it reflects both the regularity and depth of engagement necessary for effective decision-making and community contribution.

Social Capital (SCPC): The findings indicate that community identity has a small but significant effect on both informational and emotional support, while community trust does not. This suggests that in OPSCs, social capital plays a more limited role compared to human and decisional capital. Community identity encourages prosocial behaviors (Staub et al., 1984), but its impact is modest due to the platform's focus on information exchange over emotional bonding (Roland and Tirole, 2006). As members assume expert roles, their contributions are driven more by knowledge-sharing than by deep emotional connections (Blank et al., 2010), making social capital a secondary factor in their participation.

Human Capital (HCPC): The findings highlight a clear division of roles within human capital (HCPC): Professional knowledge has the strongest impact on informational support ($\beta = 0.303$), showing that members with expertise effectively reduce uncertainty and solve problems, aligning them with more technical, expert-driven roles; Common language plays a key role in emotional support ($\beta = 0.169$, $p = 0.000$), facilitating emotional connections through shared communication styles, enabling empathy and care. This underscores the dual nature of HCPC, where knowledge serves informational needs and language fosters emotional bonds, reflecting the multi-faceted contributions of members.

Moderating Effect of Identity Rights: Identity rights positively moderate the effects of both DCPC and HCPC on social support (Models 3 to 14). As a member's identity rights increase, the influence of their professional capital on social support also grows. This suggests that high-level members, through the accumulation of professional capital, gain more opportunities and status within the community, prompting them to exhibit greater social support behaviors. This finding supports the use of identity rights as a criterion for user segmentation in OPSCs (Zhang et al., 2020b).

Control Variables: The community tenure of a member negatively affects their provision of social support, aligning with the observation that user engagement tends to decline over time in virtual communities (Zhang et al., 2017b). This is particularly relevant in chronic disease communities, where users are highly engaged when their disease is newly diagnosed but reduce activity as their condition stabilizes (Reynolds et al., 2018). Additionally, we found that external incentives in the form of monetary incentives does not significantly impact the production of informational or emotional support, reinforcing that patients' social support behaviors are driven more by prosocial motivations than financial rewards.

5.2 Theoretical implications

Building on the findings and analysis, this study provides several expanded theoretical contributions that enhance our understanding of social support provision within online patient support communities (OPSCs), particularly through the lens of social identity theory and professional capital.

First, this research deepens the application of social identity theory by showing how community participants develop a doctor-like identity through their accumulated professional capital. This extends the theory beyond its traditional organizational and social contexts, applying it in a healthcare environment where patients assume expert-like roles. By identifying with the community and perceiving themselves as quasi-professional contributors, members are motivated to provide both informational and emotional support (Stewart Loane and Webster, 2017). This finding offers a new perspective on how self-concept and group identity are shaped in patient-driven healthcare models, where professional expertise emerges organically through experience.

Second, while previous studies have demonstrated the importance of doctors' professional capital in online health communities—helping them gain social and economic benefits (Guo et al., 2017) and improve performance (Wang et al., 2023)—this study reveals that OPSC members also develop professional capital and use it to provide social support. This study also expands the professional capital framework—previously used to describe the skills and influence of formal professionals like doctors—by demonstrating how non-professional community members in OPSCs develop and utilize their own forms of professional capital. The research shows that human capital (HCPC), such as professional knowledge and common language, and decisional capital (DCPC), represented by interaction frequency and intensity, significantly influence the provision of social support (Zhou, 2020). Importantly, social capital (SCPC), particularly community identity, plays a role in fostering emotional connections, albeit more modestly (Chen et al., 2020a). This reconceptualization of professional capital highlights how informal expertise—derived from personal experience with chronic illness—can drive meaningful contributions in health-focused online communities.

Third, the study highlights the effectiveness of social incentive mechanisms—such as identity rights—over traditional monetary incentives in encouraging social support behaviors in OPSCs. By demonstrating how higher community status and rights enhance members' ability to provide support as they accumulate professional capital, the research offers valuable insights into the design of community structures(Mpinganjira, 2019). This finding supports the notion that prosocial behavior in OPSCs is driven more by intrinsic motivations such as community recognition and identity rather than by external rewards. This shift away from monetary incentives offers a new approach to fostering long-term engagement and support within virtual health communities, reinforcing the importance of social belonging and identity (Panzarasa et al., 2020).

Finally, this research contributes to the evolving discourse on patient-driven healthcare models by highlighting how professional capital and social identity intersect to create a more empowered patient role in online communities. The findings suggest that as patients acquire knowledge and decisional abilities, they transition from passive recipients of care to active participants who share their expertise with others. This transformation supports the democratization of healthcare, where patients assume leadership and supportive roles typically associated with professional caregivers. By exploring how professional capital is leveraged in OPSCs, the study adds to the understanding of how digital platforms can reshape traditional healthcare dynamics and promote patient-led community support (Guo et al., 2017; Kingod et al., 2017).

5.3 Practical implications

This study's findings on professional capital provide key insights for improving OPSC platform design and social support provision. The implications can be organized into three main areas:

Leveraging Professional Capital to Enhance Social Support: The concept of professional capital—encompassing members' accumulated knowledge, skills, and experience—offers key practical insights for OPSC platform design. To maximize the impact of professional capital on social support provision, platforms should create mechanisms to identify and recognize members with significant professional capital who can serve as community advisors. These members, often seen as experts by their peers due to their accumulated medical knowledge and personal experience, can be encouraged to share information and advice in dedicated spaces. Moreover, members with strong community engagement skills can be given roles that emphasize emotional support, such as leading real-time chatrooms or discussion groups. These features should be designed to enable open, empathetic communication that strengthens emotional bonds among community members, helping them feel supported both cognitively and emotionally.

Optimizing Membership Segmentation for Greater Social Support: The study highlights the importance of membership-based identity rights in motivating members to contribute social support. OPSC practitioners should focus on membership segmentation to maximize the benefits of professional capital. By developing a tiered membership structure, platforms can assign roles and responsibilities to higher-level members, such as leading support groups or mentoring new members. This segmentation can foster a sense of community identity and prompt members to contribute more actively to both informational and emotional support.

Utilizing Text Mining for Personalized User Engagement: The integration of text mining aligns with the concept of professional capital by enabling platforms to better harness members' accumulated expertise and social dynamics. By using machine learning algorithms to analyze interaction records, OPSC platforms can automatically identify users' informational and emotional support needs, which are closely tied to their professional knowledge and community engagement. This allows the platform to match members with similar conditions or levels of expertise, fostering more personalized and relevant interactions. In turn, this enhances peer matching and deepens communication, optimizing how members with strong professional capital contribute their knowledge and emotional support to the community, making the platform more engaged and supportive overall.

5.4 Limitations and future directions

Although this study has produced interesting findings and contributes to both theory and practice, there are still some limitations that reveal where future research is needed. First, the research data used in this study is collected from a Chinese OPSC. The sample is limited to patients with one specific chronic disease (Type 2 diabetes), and our conclusions are not yet confirmed in other OPSCs for other specific diseases (such as cancer or heart disease). Second, due to the constraints of our target OPSC's functions, this work mainly uses text data from historic interaction records for text mining. The data acquisition period is short, and time effects or individual fixed effects are not considered. In future work, the data set can be further improved upon to build a panel data analysis. Third, there is still room for improvement in the trained machine learning model for social support category classification and similarity calculation. Fourth, by lagging the dependent variables behind the independent variables, we reduce the two-way causal relationship between variables. However, endogeneity is still unavoidable. Future research could more rigorously address this concern by adopting instrumental variable (IV) approaches, which help isolate exogenous variation in the independent variables. Potential instruments may include platform-generated variables (e.g., randomized exposure to health content, interface changes, or timing of platform-level nudges). Beyond IV estimation, future studies can also incorporate structural equation modeling (SEM) and path analysis to explore mediating and moderating mechanisms. Latent variable modeling may be employed to capture unobservable constructs such as motivation, empathy, or perceived group norms that influence social support behavior. To examine the temporal interdependence between components of professional capital and their dynamic relationship with social support, structural panel vector autoregression (SPVAR) models could be applied, enabling researchers to capture bidirectional feedback across time within a unified framework. Fifth, this study focuses on how professional capital influences social support by emphasizing its role in identity construction. Future research could further examine how the three dimensions of professional capital are developed and reinforced, especially by exploring the underlying cognitive mechanisms that contribute to perceived professional identity. For instance, methods such as concept-level knowledge mapping or semantic network analysis may offer insights into how users accumulate and structure knowledge of varying breadth and depth, and how these knowledge configurations enhance their role salience and perceived credibility in online support settings. Finally, qualitative research methods (e.g., interviews or participatory observation) may enrich our understanding of how users perceive privacy risks, develop trust, and engage in support behaviors in online patient communities.

6 Conclusions

This study provides a comprehensive analysis of the role professional capital plays in social support provision within Online Patient Support Communities (OPSCs). Through the lens of Social Identity Theory and leveraging large-scale empirical data, we explored the impact of the three dimensions of professional capital of members to provide both informational and emotional support.

By applying social identity theory, this research leverages empirical data from an OPSC to measure the role of professional capital in social support provision. We used advanced techniques such as text classification, LDA topic modeling, and professional dictionary matching through natural language processing to assess the levels of professional capital and social support among members. Our hypotheses were tested using multiple regression analyses.

The findings reveal that both decisional capital (DCPC) and human capital (HCPC) have significant positive effects on members' provision of informational and emotional support. However, social capital (SCPC) shows limited influence, suggesting that social support behaviors in OPSCs are driven by prosocial motivations rather than traditional social relationship factors. Additionally, the member's level (reflecting community status and rights) positively moderates the impact of professional capital on social support, indicating that higher-level members contribute more actively.

In conclusion, this study advances our understanding of how professional capital influences social support behaviors in OPSCs. It highlights the unique motivations—professional capital— behind patient-driven support and provides practical insights for improving OPSC management. These include optimizing member recognition systems, enhancing peer-to-peer engagement, and developing features that leverage members' expertise to foster a more supportive community environment. The findings offer a roadmap for creating more effective and sustainable online health communities that better meet the needs of their participants.

Appendix A: Annotation process

In this study, we conducted a detailed manual annotation of user interactions from online communities for diabetes patients, aiming to categorize each post into one of two types of social support: emotional support and informational support.

1) ***Emotional_support*** refers to expressions of empathy, encouragement, or psychological comfort, such as "I completely understand how you feel" or "Keep going, you can do this."

2) ***Informational_support*** includes actionable advice, health knowledge, or medication guidance, such as "Walking 30 minutes a day helps control blood sugar" or "This medication should be taken after meals."

To ensure scientific rigor, we developed comprehensive annotation guidelines in collaboration with medical experts specializing in diabetes management. These guidelines included precise definitions, representative examples, and rule-based decision criteria to support consistent interpretation. They were iteratively refined through several rounds of pilot annotation to enhance clarity and applicability.

The annotation process followed a systematic workflow:

1) ***Independent Annotation:*** Two trained annotators independently labeled the same set of text segments.

2) ***Adjudication:*** Disagreements were resolved by a third expert adjudicator with specialized knowledge in diabetes care. Final decisions were made based on established guidelines and contextual interpretation.

3) ***Reliability_Assessment:*** Inter-rater reliability between the two annotators was assessed using Cohen's Kappa, resulting in a score of 0.89, indicating a high level of agreement.

Competing Interests The authors declare that they have no competing interests.

References

Alemu E N, Huang J (2020). HealthAid: Extracting domain targeted high precision procedural knowledge from on-line communities. Information Processing & Management, 57(6): 102299

Andrews K M, Delahaye B L (2002). Influences on knowledge processes in organizational learning: The psychosocial filter. Journal of Management Studies, 37(6): 797–810

Ardichvili A, Page V, Wentling T (2003). Motivation and barriers to participation in virtual knowledge-sharing communities of practice. Journal of Knowledge Management, 7(1): 64–77

Argyle M (1978). The Psychology of Interpersonal Behaviour. United Kingdom: Penguin Press

Barak A, Boniel-Nissim M, Suler J (2008). Fostering empowerment in online support groups. Computers in Human Behavior, 24(5): 1867–1883

Blank T O, Schmidt S D, Vangsness S A, Monteiro A K, Santagata P V (2010). Differences among breast and prostate cancer online support groups. Computers in Human Behavior, 26(6): 1400–1404

Brashers D E, Neidig J L, Goldsmith D J (2004). Social support and the management of uncertainty for people living with HIV or AIDS. Health Communication, 16(3): 305–331

Brown J S, Duguid P (2001). Knowledge and organization: A social-practice perspective. Organization Science, 12(2): 198–213

Butler B S (2001). Membership size, communication activity, and sustainability: A resource-based model of online social structures. Information Systems Research, 12(4): 346–362

Carron-Arthur B, Ali K, Cunningham J A, Griffiths K M (2015). From help-seekers to influential users: A systematic review of participation styles in online health communities. Journal of Medical Internet Research, 17(12): e271

Cassell J, Tversky D (2005). The language of online intercultural community formation. Journal of Computer-Mediated Communication, 10(2): JCMC1027

Chang H H, Chuang S S (2011). Social capital and individual motivations on knowledge sharing: Participant involvement as a moderator. Information & Management, 48(1): 9–18

Chen L, Baird A, Straub D (2020a). A linguistic signaling model of social support exchange in online health communities. Decision Support Systems, 130: 113233

Chen S, Guo X, Wu T, Ju X (2020b). Exploring the online doctor-patient interaction on patient satisfaction based on text mining and empirical analysis. Information Processing & Management, 57(5): 102253

Chen Y, Feeley T H (2014). Social support, social strain, loneliness, and well-being among older adults: An analysis of the health and retirement study. Journal of Social and Personal Relationships, 31(2): 141–161

Child S (2016). Social Capital and Social Networks: The Importance of Social Ties for Health among Residents of Disadvantaged Communities. Dissertation for the Doctoral Degree. University of South Carolina, USA

Chiu C M, Hsu M H, Wang E T (2006). Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories. Decision Support Systems, 42(3): 1872–1888

Chuang K Y, Yang C C (2010). Helping you to help me: Exploring supportive interaction in online health community. Proceedings of the American Society for Information Science and Technology, 47(1): 1–10

Cobb S (1976). Social support as a moderator of life stress. Biopsychosocial Science and Medicine, 38(5): 300–314

Cohen S, Underwood L G, Gottlieb B H (2000). Social support measurement and intervention: A guide for health and social scientists. New York: Oxford University Press

Coulson N S (2013). How do online patient support communities affect the experience of inflammatory bowel disease? An online survey. JRSM Short Reports, 4(8): 2042533313478004

Dang Y, Guo S, Guo X, Vogel D (2020). Privacy protection in online health communities: Natural experimental empirical study. Journal of Medical Internet Research, 22(5): e16246

Dang Y, Guo S, Guo X, Wang M, Xie K (2021). Privacy concerns about health information disclosure in mobile health: Questionnaire study investigating the moderation effect of social support. JMIR mHealth and uHealth, 9(2): e19594

Dang Y, Guo S, Song H, Li Y (2024). Setting goal difficulty in monetary incentives to physicians: Evidence from an online health knowledge-sharing platform. Information Technology & People, 37(2): 605–634

Davis J L, Love T P, Fares P (2019). Collective social identity: Synthesizing identity theory and social identity theory using digital data. Social Psychology Quarterly, 82(3): 254–273

Dinev T, Hart P (2006). An extended privacy calculus model for e-commerce transactions. Information Systems Research, 17(1): 61–80

Dutton J E, Dukerich J M, Harquail C V (1994). Organizational images and member identification. Administrative Science Quarterly, 39(2): 239–263

Ellemers N, De Gilder D, Haslam S A (2004). Motivating individuals and groups at work: A social identity perspective on leadership and group performance. Academy of Management Review, 29(3): 459–478

Ellemers N, Kortekaas P, Ouwerkerk J W (1999). Self-categorisation, commitment to the group and group self-esteem as related but distinct aspects of social identity. European Journal of Social Psychology, 29: (2–3): 371–389

Frost J H, Massagli M P (2008). Social uses of personal health information within PatientsLikeMe, an online patient community: What can happen when patients have access to one another's data. Journal of Medical Internet Research, 10(3): e15

Fullan M, Rincón-Gallardo S, Hargreaves A (2015). Professional capital as accountability. Education Policy Analysis Archives, 23: 15–15

Galegher J, Sproull L, Kiesler S (1998). Legitimacy, authority, and community in electronic support groups. Written Communication, 15(4): 493–530

Granovetter M (1985). Economic action and social structure: The problem of embeddedness. American Journal of Sociology, 91(3): 481–510

Guo S, Chen Y, Dang Y, Li X (2025). Individual protective actions with social support seeking in an online health community: Two observational cross-sectional studies during public health emergencies. Humanities & Social Sciences Communications, 12(1): 550

Guo S, Guo X, Fang Y, Vogel D (2017). How doctors gain social and economic returns in online health-care communities: A professional capital perspective. Journal of Management Information Systems, 34(2): 487–519

Guo S, Guo X, Zhang X, Vogel D (2018). Doctor–patient relationship strength's impact in an online healthcare community. Information Technology for Development, 24(2): 279–300

Guo X, Guo S, Vogel D, Li Y (2016). Online healthcare community interaction dynamics. Journal of Management Science and Engineering, 1(1): 58–74

Håkansson J, Montgomery H, and the HåKansson J (2003). Empathy as an interpersonal phenomenon. Journal of Social and Personal Relationships, 20(3): 267–284

Hale B J, Gonzales A L, Richardson M (2018). Vlogging cancer: Predictors of social support in YouTube cancer vlogs. Cyberpsychology, Behavior, and Social Networking, 21(9): 575–581

Hargreaves A, Fullan M (2013). The power of professional capital. Learning Professional, 34(3): 36

Hargreaves A, Fullan M (2015). Professional Capital: Transforming Teaching in Every School. Teachers College Press

Helgeson V S (2003). Social support and quality of life. Quality of Life Research: An International Journal of Quality of Life Aspects of Treatment, Care and Rehabilitation, 12(S1): 25–31

Hogg M A, Terry D I (2000). Social identity and self-categorization processes in organizational contexts. Academy of Management Review, 25(1): 121–140

Huang K, Chengalur-Smith I, Ran W (2013). Engagement in healthcare virtual support communities: Social support, companionship activities, and gender differences. Communications of the Association for Information Systems: 34

Huang K Y, Chengalur-Smith I, Pinsonneault A (2019). Sharing is caring: Social support provision and companionship activities in healthcare virtual support communities. Management Information Systems Quarterly, 43(2): 395–423

Huang K Y, Chengalur-Smith I, Ran W (2014). Not just for support: Companionship activities in healthcare virtual support communities. Communications of the Association for Information Systems, 34(1): 29

Jiang L C, Bazarova N N, Hancock J T (2011). The disclosure–intimacy link in computer-mediated communication: An attributional extension of the hyperpersonal model. Human Communication Research, 37(1): 58–77

Jin X L, Yin M, Zhou Z, Yu X (2021). The differential effects of trusting beliefs on social media users' willingness to adopt and share health knowledge. Information Processing & Management, 58(1): 102413

Kawachi I, Berkman L F (2001). Social ties and mental health. Journal of Urban Health, 78(3): 458–467

Kazmer M M, Lustria M L A, Cortese J, Burnett G, Kim J H, Ma J, Frost J (2014). Distributed knowledge in an online patient support community: Authority and discovery. Journal of the Association for Information Science and Technology, 65(7): 1319–1334

Kim H W, Zheng J R, Gupta S (2011). Examining knowledge contribution from the perspective of an online identity in blogging communities. Computers in Human Behavior, 27(5): 1760–1770

King G, Willoughby C, Specht J A, Brown E (2006). Social support processes and the adaptation of individuals with chronic disabilities. Qualitative Health Research, 16(7): 902–925

Kingod N, Cleal B, Wahlberg A, Husted G R (2017). Online peer-to-peer communities in the daily lives of people with chronic illness: A qualitative systematic review. Qualitative Health Research, 27(1): 89–99

Knippenberg A D (1991). Social identifications: A social psychology of intergroup relations and group processes. British Journal of Social Psychology, 30(3): 271–272

Koetsenruijter J, van Eikelenboom N, van Lieshout J, Vassilev I, Lionis C, Todorova E, Portillo M C, Foss C, Gil M S, Roukova P (2016). Social support and self-management capabilities in diabetes patients: An international observational study. Patient Education and Counseling, 99(4): 638–643

Lekwijit S, Terwiesch C, Asch D A, Volpp K G (2024). Evaluating the efficacy of connected healthcare: An empirical examination of patient engagement approaches and their impact on readmission. Management Science, 70(6): 3417–3446

Liao G Y, Huang T L, Dennis A R, Teng C I (2024). The influence of media capabilities on knowledge contribution in online communities. Information Systems Research, 35(1): 165–183

Liu C, Marchewka J T, Lu J, Yu C S (2005). Beyond concern—A privacy-trust-behavioral intention model of electronic commerce. Information & Management, 42: (2): 289–304

Liu J, Zhang X, Meng F, Lai K (2020). Deploying gamification to engage physicians in an online health community: An operational paradox. International Journal of Production Economics, 228: 107847

Mao J Y, Benbasat I (2000). The use of explanations in knowledge-based systems: Cognitive perspectives and a process-tracing analysis. Journal of Management Information Systems, 17: (2): 153–179

McCaig D, Elliott M T, Siew C S, Walasek L, Meyer C (2019). Profiling commenters on mental health–related online forums: A methodological example focusing on eating disorder–related commenters. JMIR Mental Health, 6(4): e12555

Mpinganjira M (2019). Willingness to reciprocate in virtual health communities: The role of social capital, gratitude and indebtedness. Service Business, 13(2): 269–287

Nahapiet J, Ghoshal S (1998). Social capital, intellectual capital, and the organizational advantage. Academy of Management Review, 23(2): 242–266

Nonnecke B, Preece J (2003). Silent Participants: Getting to Know Lurkers Better. London: Springer London

O'Neill B, Ziebland S, Valderas J, Lupiáñez-Villanueva F (2014). User-generated online health content: A survey of Internet users in the United Kingdom. Journal of Medical Internet Research, 16(4): e118

Ommen O, Thuem S, Pfaff H, Janssen C (2011). The relationship between social support, shared decision-making and patient's trust in doctors: A cross-sectional survey of 2,197 inpatients using the Cologne Patient Questionnaire. International Journal of Public Health, 56(3): 319–327

Panzarasa P, Griffiths C J, Sastry N, De Simoni A (2020). Social medical capital: How patients and caregivers can benefit from online social interactions. Journal of Medical Internet Research, 22(7): e16337

Pavlou P A, Gefen D (2004). Building effective online marketplaces with institution-based trust. Information Systems Research, 15(1): 37–59

Rains S A (2016). Language style matching as a predictor of perceived social support in computer-mediated interaction among individuals coping with illness. Communication Research, 43(5): 694–712

Rains S A, Peterson E B, Wright K B (2015). Communicating social support in computer-mediated contexts: A meta-analytic review of content analyses examining support messages shared online among individuals coping with illness. Communication Monographs, 82(4): 403–430

Rains S A, Young V (2009). A meta-analysis of research on formal computer-mediated support groups: Examining group characteristics and health outcomes. Human Communication Research, 35(3): 309–336

Reynolds R, Dennis S, Hasan I, Slewa J, Chen W, Tian D, Bobba S, Zwar N (2018). A systematic review of chronic disease management interventions in primary care. BMC Family Practice, 19(1): 11

Roland B, Tirole J (2006). Incentives and prosocial behavior. American Economic Review, 96(5): 1652–1678

Ryan V D, Agnitsch K A, Zhao L, Mullick R (2005). Making sense of voluntary participation: A theoretical synthesis. Rural Sociology, 70(3): 287–313

Sarason I G, Levine H M, Basham R B, Sarason B R (1983). Assessing social support: The social support questionnaire. Journal of Personality and Social Psychology, 44(1): 127–139

Shaw B R, McTavish F, Hawkins R, Gustafson D H, Pingree S, and the Bret R. Shaw, Fiona McTavish, Rober (2000). Experiences of women with breast cancer: Exchanging social support over the CHESS computer network. Journal of Health Communication, 5(2): 135–159

Shensa A, Sidani J E, Escobar-Viera C G, Switzer G E, Primack B A, Choukas-Bradley S (2020). Emotional support from social media and face-to-face relationships: Associations with depression risk among young adults. Journal of Affective Disorders, 260: 38–44

Shinn M, Lehmann S, Wong N W (1984). Social interaction and social support. Journal of Social Issues, 40(4): 55–76

Shumaker S A, Brownell A (1984). Toward a theory of social support: Closing conceptual gaps. Journal of Social Issues, 40(4): 11–36

Song X, Liu Y H, Jin J, Zhao J (2018). Factors driving continued use of online health promotion competitions. Online Information Review, 42(6): 802–820

Staub E, Bar-Tal D, Karylowski J, Reykowski J (1984). Development and Maintenance of Prosocial Behavior: International Perspectives on Positive Morality. New York: Plenum Publishing Corporation

Stewart S A, Abidi S S R (2012). Applying social network analysis to understand the knowledge sharing behaviour of practitioners in a clinical online discussion forum. Journal of Medical Internet Research, 14(6): e170

Stewart Loane S, Webster C M (2017). Social capital and consumer value co-created within an online health community. Journal of Nonprofit & Public Sector Marketing, 29(3): 317–345

Suhay E (2015). Explaining group influence: The role of identity and emotion in political conformity and polarization. Political Behavior, 37(1): 221–251

Tajfel H (1974). Social identity and intergroup behaviour. Social Sciences Information. Information Sur les Sciences Sociales, 13(2): 65–93

Tamjidyamcholo A, Baba M S B, Shuib N L M, Rohani V A (2014). Evaluation model for knowledge sharing in information security professional virtual community. Computers & Security, 43: 19–34

Tsai W, Ghoshal S (1998). Social capital and value creation: The role of intrafirm networks. Academy of Management Journal, 41(4): 464–476

Turner J W, Robinson J D, Tian Y, Neustadtl A, Angelus P, Russell M, Mun S K, Levine B (2013). Can messages make a difference? The association between e-mail messages and health outcomes in diabetes patients. Human Communication Research, 39(2): 252–268

Vahtera P, Buckley P J, Aliyev M, Clegg J, Cross A R (2017). Influence of social identity on negative perceptions in global virtual teams. Journal of International Management, 23(4): 367–381

Van Dick R (2001). Identification in organizational contexts: Linking theory and research from social and organizational psychology. International Journal of Management Reviews, 3(4): 265–283

Van Dick R, Wagner U, Stellmacher J, Christ O (2005). Category salience and organizational identification. Journal of Occupational and Organizational Psychology, 78(2): 273–285

Wang J J, Liu H, Ye J (2023). The impact of individual and team professional capital on physicians' performance in online health-care communities: a cross-level investigation. Internet Research, 33(1): 152–177

Wang Q, Qiu L, Xu W (2024). Informal payments and doctor engagement in an online health community: An empirical investigation using generalized synthetic control. Information Systems Research, 35(2): 706–726

Wang W T, Wei Z H (2011). Knowledge sharing in wiki communities: An empirical study. Online Information Review, 35(5): 799–820

Wasko M M, Faraj S (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. Management Information Systems Quarterly, 29(1): 35–57

Wellman B, Wortley S. (1989). Brothers' keepers: Situating kinship relations in broader networks of social support. Sociological Perspectives, 32(3): 273–306

Wright K B (2016). Communication in health-related online social support groups/communities: A review of research on predictors of participation, applications of social support theory, and health outcomes. Review of Communication Research, 4: 65–87

Wright K B, Bell S B, Wright K B, Bell S B (2003). Health-related support groups on the Internet: Linking empirical findings to social support and computer-mediated communication theory. Journal of Health Psychology, 8(1): 39–54

Wu B (2018). Patient continued use of online health care communities: Web mining of patient-doctor communication. Journal of Medical Internet Research, 20(4): e126

Wu J, Hou S, Jin M (2017). Social support and user roles in a chinese online health community: A LDA based text mining study. In: International Conference on Smart Health. Cham: Springer International Publishing, 10347: 169–176

Wu L (2013). Social network effects on productivity and job security: Evidence from the adoption of a social networking tool. Information Systems Research, 24(1): 30–51

Yan L, Tan Y (2014). Feeling Blue? Go online: An empirical study of social support among patients. Information Systems Research, 25(4): 690–709

Yang F, Zhong B, Kumar A, Chow S M, Ouyang A (2018). Exchanging social support online: A longitudinal social network analysis of irritable bowel syndrome patients' interactions on a health forum. Journalism & Mass Communication Quarterly, 95(4): 1033–1057

Yang H, Yan Z, Jia L, Liang H (2021). The impact of team diversity on physician teams' performance in online health communities. Information Processing & Management, 58(1): 102421

Yang Y, Zhang X, Lee P K C (2019). Improving the effectiveness of online healthcare platforms: An empirical study with multi-period patient-doctor consultation data. International Journal of Production Economics, 207: 70–80

Yli-Renko H, Autio E, Sapienza H J (2001). Social capital, knowledge acquisition, and knowledge exploitation in young technology - based firms. Strategic Management Journal, 22: (6–7): 587–613

Zaphiris P, Ang C S (2009). Social Computing and Virtual Communities. New York: CRC Press

Zhang N, Jia Q, Yin K, Dong L, Gao F, Hua N (2020a). Conceptualized representation learning for chinese biomedical text mining. arXiv preprint arXiv: 10813

Zhang X, Liu S, Deng Z, Chen X (2017a). Knowledge sharing motivations in online health communities: A comparative study of health professionals and normal users. Computers in Human Behavior, 75: 797–810

Zhang Y, Li X, Fan W (2020b). User adoption of physician's replies in an online health community: An empirical study. Journal of the Association for Information Science and Technology, 71(10): 1179–1191

Zhang Y, Sun Y, Kim Y (2017b). The influence of individual differences on consumer's selection of online sources for health information. Computers in Human Behavior, 67: 303–312

Zhao Y, Da J, Yan J (2021). Detecting health misinformation in online health communities: Incorporating behavioral features into machine learning based approaches. Information Processing & Management, 58(1): 102390

Zhou J, Zhang Q, Zhou S, Li X, Zhang X M (2023). Unintended emotional effects of online health communities: A text mining-supported empirical study. Management Information Systems Quarterly, 47(1): 195–226

Zhou T (2020). Understanding users' participation in online health communities: A social capital perspective. Information Development, 36(3): 403–413

Zhu P, Shen J, Xu M (2020). Patients' willingness to share information in online patient communities: Questionnaire study. Journal of Medical Internet Research, 22(4): e16546