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Developing social capital through professionally oriented social network sites

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ABSTRACT

To date, research on social network sites (SNSs) has primarily focused on Facebook. Professionally oriented social network sites (P-SNSs), such as LinkedIn, have been under-researched in the information systems discipline. Additionally, little is known about the effects of important elements of SNSs (such as one's profile) on social capital formation. As such, the main objective of this research is to propose and validate a model that explains the process by which individuals develop and accrue social capital through P-SNS use. This model draws upon social capital theory and social network analysis and is validated through a survey of 377 LinkedIn users. Our results find that (1) P-SNS users' actions (perceived profile disclosure, active participation, and passive consumption) have significant positive effects on perceived social connectedness; (2) perceived social connectedness on P-SNSs has a significant positive effect on perceived networking value on these sites; (3) perceived profile disclosure and passive consumption have significant positive effects on network size; (4) active participation does not have any effect on network size, and (5) network size does not have a significant effect on perceived networking value. Overall, this investigation advances our understanding of how social capital is formed in P-SNSs. Additionally, this is the first study in the P-SNS context that investigates the role of the user profile in the social capital formation process, along with user actions of active participation and passive consumption. From a practical perspective, this study has implications for different audiences, such as job seekers, recruiters, and P-SNS providers, assisting them in playing a more effective role in the social capital formation process on P-SNSs.

1. Introduction

Social network sites (SNSs) such as Facebook, LinkedIn, and Twitter are a new class of information technology that support interpersonal communication and collaboration using Internet-based platforms [40]. In recent years, we have witnessed the rapid diffusion of SNSs. As of July 2020, more than 3.9 billion people, i.e., half of the world's population, actively use SNSs, spending on average 140 min per day on these sites [30, 38]. Interestingly, SNSs usage is not limited to younger adults anymore, as was the case in the early adoption of such sites. From 2011 to 2019, SNSs use by American adults ages 30–49 increased from 60% to 82%, while for those ages 50–64, the increase was from 37% to 69%, and for those 65 and above, it was from 14% to 40% [68]. SNSs are also widely used among professionals. LinkedIn, as the world's largest professionally oriented SNS (P-SNS) with more than 706 million members, now plays an important role in connecting professionals all around the world [58, 102]. Thus, SNSs have become part of our everyday lives, changing various aspects of our daily routines such as the way we communicate with each other, access information, develop relationships, and spend our free time [69, 79]. However, since the beginning of SNSs' wide adoption in 2003 [11], the question of whether and how people can gain tangible benefits from using these sites has drawn the attention of scholars as well as policymakers.

To respond to this question, a stream of information systems (IS) research has sought to understand the benefits of using SNSs under the framework of social capital and social network theories ([24, 25, 39, 81, 92]). These theories explain how individuals' actions to extend and diversify their social networks, as well as improve the quality of their relationships, can lead to access to new information, opportunities, perspectives, and increased social support. While some studies of SNSs showed relationships between the use of SNSs and negative outcomes such as loneliness [18], others have found positive relationships between specific social activities such as network construction and content generation and social capital outcomes [14]. However, the extant SNSs

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literature concerning social capital suffers from several gaps.

First, most SNS research focuses on socially oriented social networking sites (S-SNSs), such as Facebook, which limits the depth and breadth of understanding of how social capital forms in SNSs [101]. While some aspects of the social capital formation process (e.g., resource exchange) may be more relevant to P-SNSs compared to S-SNSs, there are limited studies that investigate this process on such sites. In general, P-SNSs are under-researched in IS [6, 60, 102].

Second, current studies do not include the effects of one's profile on the social capital formation process [27]. In P-SNSs, one's profile is akin to an online resume and can help users to expand their professional networks by establishing a common ground for professional self-promotion. Very few studies have examined the impact of users' profiles on these platforms (either S-SNS or P-SNS).

Third, while many studies investigate the relationships between SNS use and social capital outcomes, only a few studies have considered the role of social capital sources [47]. Social capital sources lie in the structure and content of the social network and should be differentiated from social capital outcomes [56, 72, 86]. According to Lin [55, 56], social capital sources should be considered necessary and important antecedents to social capital outcomes. Sources of social capital, such as a larger network size or social connectedness, result from individuals' actions or investments in their social networks ([54]; 2002). As such, the mediating role of social capital sources between user actions and social capital outcomes needs to be further understood [47].

Addressing these aforementioned gaps can increase the generalizability of social capital research in digital environments. Moreover, with social distancing restrictions due to the ongoing COVID-19 pandemic, traditional face-to-face networking is more challenging, and thus developing social capital through the online world becomes more critical for both individuals and organizations. It is likely that this will continue to be important in the post-pandemic era where there will be more emphasis and reliance on working from home and online professional activities and networking [17, 22]. As individuals increasingly turn to online networking and perceive the value of social capital formation on P-SNS, they will place more emphasis on creating rich and complete profiles. This will help organizations to find the best candidates to meet their goals, which further increases the value of P-SNSs for organizations. This, in turn, will result in individuals' placing further emphasis on their P-SNS social capital formation. It is expected that this cyclical relationship will become stronger and more important as virtual professional network development becomes more of the norm [17]. However, current measures of online social capital (bridging and bonding social capital) were originally developed for general Internet users [97] and may not be as relevant in today's context of P-SNS. As such, there is a need to understand the P-SNS social capital formation process in a digitally focused professional network environment. Thus, the overarching question of this research is as follows: "What is the process by which individuals develop and accrue social capital on P-SNSs?" More specifically, this study aims to answer (1) How does user profile disclosure lead to accruing and developing social capital on P-SNSs via social capital sources? and (2) How do user actions on P-SNSs, such as active participation and passive consumption, lead to accruing and developing social capital on P-SNSs via social capital sources?

2. Social networking sites

When referring to SNSs, applications such as Facebook, Twitter, YouTube, WhatsApp, Pinterest, Instagram, and LinkedIn often come to mind [41]. These applications are driven by user-generated content and have re-established the dynamics and communication between and among individuals, organizations, and governments. Given the radical transformation of communication and the impact of SNSs on various stakeholders, these platforms have attracted the attention of researchers from diverse fields, including IS [41].

While several lenses and frameworks have been used to describe SNSs in IS, Karahanna et al. [42] provide a particularly robust affordance-based approach to understand action possibilities permitted by social media features. Through their comprehensive review of 21 popular SNS applications, they identify 12 key social media affordances grouped into egocentric and allocentric categories. Egocentric affordances reflect action possibilities that tend to be solitary in nature and do not necessitate the involvement of others to be actualized, whereas allocentric affordances reflect action possibilities that are social in nature and, thus, necessitate the involvement of others. A prominent egocentric affordance of SNSs is self-presentation, which enables users to reveal and present information related to themselves [42]. Self-presentation allows SNS users to show what kind of people they are, what they value and like, as well as their experiences and expertise. This self-presentation affordance has also been labeled as identity by Kietzmann et al. [45] and as identifiability by Halpern & Gibbs [35].

Self-presentation affordance can be provided by such features as one's SNS profile [42]. It serves as the locus of interaction and represents the individual [10]. SNS profiles support relationship development as it is a venue through which users communicate their identity information (such as their hometown, current job, and education) and highlight their shared interests (such as favorite songs, artists, and hobbies). Sharing identity information and interests establishes common ground with other people so that relationships may be developed more easily. According to Ellison & Vitak [27], one's profile can be used as a "social lubricant, smoothing social interaction by highlighting commonalities and differences". Thus, one's SNS profile can be a powerful affordance to satisfy several motivations and needs, which may be both egocentric and allocentric in nature. This is highlighted by Karahanna et al. [42] through their mapping of psychological needs to social media affordances that satisfy those needs. From their list of 12 key social media affordances, self-presentation can fulfill the greatest number of self-focused and other-focused psychological needs.

Despite its potential importance in understanding the SNS context, very few studies have examined the impacts of user profiles within these applications. To date, most IS research in this domain has focused on the behavioral side of social media, utilizing social media for user reviews, and the integration of social media for marketing and organizational purposes [41]. First, from a behavioral perspective, social media use behaviors and consequences have been investigated with emphasis on the dysfunctional consequences of addiction, stress, information overload, among others (e.g., [88]). Second, user reviews of products/services have been investigated for their authenticity and efficacy as well as their general influence on decision-making processes (e.g., [48]). Third, organizational use of social media has showcased the extent to which social media is being integrated into marketing strategies (e.g., [52]) and the impact of integrating social media within work roles (e.g., [99]). Regardless of the theme or focus, Kapoor et al. [41] highlight that IS social media studies during the past two decades have most frequently targeted the following platforms: Facebook, online communities, Twitter, Blogs, and YouTube. Professionally oriented sites, such as LinkedIn, have typically not been the lens for investigating SNS phenomena. Scholarly knowledge on P-SNS is limited, scattered, and tends to focus on efficacy in human resource management practice [73].

3. Theoretical framework

The main objective of this study is to propose and validate a model that explains the process by which individuals develop and accrue social capital through the use of P-SNSs, such as LinkedIn. As such, the proposed research model draws upon the extant literature in social media (specifically SNSs), social capital theory (SCT) [20, 55, 56, 70], and social network analysis (SNA) [7, 15, 40]. While SCT explains how embedded resources (e.g., status, wealth, and power) and feelings of connectedness can affect the benefits that individuals can gain from their networks, SNA helps us to understand how individuals' different courses of action in the online context can affect those benefits.

3.1. Social capital theory

According to Coleman [20], social capital occurs in the relations among people. It exists in the form of the skills and knowledge acquired by a human and is far less tangible than physical capital, which exists in the form of observable material and human capital. Fukuyama [28] suggests that there is no consensus on a universal definition of social capital and explains it as "shared norms or values that promote social cooperation, instantiated in actual social relationships" ([28], p. 27). Putnam [71] defines social capital as "connections among individuals and the norms of reciprocity and trustworthiness that arise from them" (p.4). SCT provides a conceptual framework to understand human social behavior [21, 70] and posits that social networks have value [70]. Just like physical or human capital, social capital can increase the productivity of individuals and groups. In Putnam's (1993, 2000) conceptualization, social capital exists in two forms: (1) bridging social capital and (2) bonding social capital. While bridging social capital is associated with new information, diversity, inclusiveness, and broader identity, bonding social capital is linked to emotional support, solidarity, exclusiveness, and in-group loyalty.

Furthering earlier conceptualizations in this domain, Lin [56] takes a process approach to understand social capital formation. Lin [56] posits that "capital" in social capital should be viewed as both a concept and a theory. As a concept, it represents a valued resource and as a theory, it describes the process by which capital is established to return benefits. In this theory conceptualization, user's actions can result in sources for social capital, which in turn, can result in social capital outcomes/benefits. Lin's (2002, [56]) theory of social capital has been described as "the most well-defined and fully-described model in understanding the nature and dynamics of social capital phenomenon" ([2], p. 2).

Three key elements of Lin's conceptualization are as follows: (1) investment in social relations through individuals' instrumental or expressive actions; (2) access to embedded resources in a social structure; and (3) expected returns ([54], 2002, [56]). Instrumental-related actions are those actions taken by individuals to obtain resources not possessed by them (e.g., networking to get a better job), whereas expressive-related actions are those actions taken by individuals to maintain or enhance resources they already possess (e.g., seeking advice to preserve one's marriage) [54]. The second key element of embedded resources can be analyzed through network structure (i.e., the size of the network and an individual's location within the social structure) and network resources (i.e., the value of individuals with whom a person has direct or indirect ties in terms of wealth, power, and status). Social capital outcomes are the final key element of Lin's (2002, [56]) process approach, where four benefits are theorized: (1) information (social connections providing the individual access to useful or unique information); (2) influence (social connections influencing decisions involving the individual); (3) social credentials (social connections providing added resources to others beyond the individual's personal capital); and (4) reinforcement (social connections' acknowledgement of the individual's claim to certain resources, skills, and knowledge). These benefits can manifest in returns of wealth, power, reputation, among others [55].

Koroleva et al. [47] utilize this process approach to create a model of social capital formation on SNSs. They find that social capital sources of network structure and social connectedness fully mediate the relationship between user actions (active participation and passive following) and social capital benefits. Additionally, they define four new social capital benefits of networking value, horizon-broadening, emotional support, and offline participation. Thus, like Lin [55, 56], distancing themselves from traditional measures of bridging and bonding.

In this current investigation, we adopt the process approach to social capital formation (as per [47, 55, 56]) where we distinguish between user's actions leading to sources of social capital, resulting in social capital outcomes and benefits. This allows for a more fine-grained understanding of how actions influence outcomes on P-SNSs, which can provide insights for individuals and organizations that are increasingly relying on such tools for professional development and recruitment.

3.2. Social network analysis

As articulated by Lin [56], "social capital does not bind or bridge. It is the nature of the social networks that bind, bond or bridge" (p. 14). This is a fundamental tenant of SNA, where the network is a central construct, and one's position in the network structure helps to determine opportunities and constraints [16, 31, 40]. While the debate over whether SNA is a theory of its own or just a methodology persists in the extant literature [7, 74], there are at least two well-known theories—Granovetter's (1973) Strength of Weak Ties (SWT) theory and Burt's (1992) Structural Holes (SH) theory—that provide a rich foundation for understanding the interaction processes and mechanisms that can yield certain outcomes for individuals and groups ([7, 8]; R. [15, 31]). Both theories are built on the same underlying model of how social networks work to create ties between individuals [7], which is central to SNA. SWT theory argues that the degree of overlap of two individuals' networks is dependent on the degree to which the tie between them (the two individuals) is strong. The strength of a tie between two individuals is determined by a combination of the emotional intensity, amount of time, intimacy, and reciprocity between these two individuals. While SWT theory is based on the strength of ties to explain the extent to which a person could have access to novel information, SH theory explains the same concept, i.e., access to novel information, based on the extent to which an individual's network has SH. A SH is defined as a gap between two individuals. When an individual's network has more SH, he/she has more non-redundant ties and, as a result, has access to more novel information [7, 15]

Kane et al. [40] extend the theories and rich set of concepts in SNA to the context of social media in order to offer conceptualizations of how to understand users' actions in their online social networks as well as how social media platform design characteristics can affect benefits gained. In a social network, ties can be of different types, such as proximities (being in the same platform, group, and location), social relations (friends, families, or affective relations), interactions (messaging and discussion boards), and flows (information) [8]. While SNSs support these different types, Kane et al. [40] argue that these networks undermine the traditional relationships theorized by SNA between these tie types. In traditional SNA, tie types represent a continuum, where each serves as the foundation for the next [5]. In SNSs, these different tie types are typically decoupled from one another. For example, on the S-SNS of Twitter, flows (Twitter trends) and social relations (Twitter followers) can both occur without interactions or proximities.

Ties also have specific characteristics such as degree (the total number of connections maintained by a node), symmetry (whether both nodes in a dyad reciprocate a tie), affect (whether or not two nodes "like" or "dislike" each other), and strength (the frequency and depth with which two nodes interact). Tie types and characteristics are determined from the design choice of platforms. These factors influence the network structure, and, as a result, they may affect people's ability to access new information. For example, Kane et al. [40] highlight the network structure differences between the SNSs of Twitter and LinkedIn, due to the impact that design choices have had on these platform's tie types and characteristics. The design on LinkedIn requires verification and reciprocity of connections when creating ties. This is not the case on Twitter where followers are not verified nor require reciprocation. As such, one's network on LinkedIn tends to be more homogeneous compared to Twitter, with less diverse but more personal information sharing.

In addition to tie type and characteristics, SNA examines a network's content, which are the resources available in the network. Borgatti & Foster (2003) refer to SNA contagion theories when investigating how interactions with network content exert effects on individuals who interact with that content. Like a biological pathogen, content can spread through a social network and influence those who come in contact with it. In the context of SNSs, Kane et al. [40] argue that one's digital profile (which reflects the user's identity in the network) flows through the network and "represents the content through which the user influences and is influenced by others" (p.287). Ellison and Boyd (2013) identify three sources of content in the user profile—content type, digital activity trace, and third-party contributions—and Kane et al. [40] suggest that these sources affect how content flows and spreads in SNSs. While research on SNS users' profiles is still nascent, it is understood that these profiles have important implications for content flow and impact in the network [42]. For the current investigation, SNA helps us understand how SNSs work to create ties and content through user actions. These user actions may lead to social capital sources and ultimately to social capital benefits.

4. Research model and hypotheses

Fig. 1 shows the research model based on the theoretical foundation discussed in the previous section. The core concept underlying this research model is that people purposefully use P-SNSs to invest in their social networks by performing various actions such as disclosing their personal information through their profiles, active participation, and passive consumption. This can lead to developing sources of social capital (specifically, network size and social connectedness), which in turn, can provide valuable benefits (specifically, networking value). We note that this is not meant to be a complete representation of possible user actions, social capital sources, and social capital benefits for P-SNS users. Rather we chose to investigate constructs that were particularly relevant to the P-SNS context, could be theoretically supported, and yet were under-researched in this domain. We chose a parsimonious approach to investigate the social capital formation, which has a rich history as a guiding principle for inference (e.g., [36, 51, 76, 95]). While larger models with many constructs and associations may provide a more complete representation of the phenomenon under investigation, they require larger sample sizes, longer questionnaires (resulting in lower response rates), and tend to suffer from lack of focus [51, 95]. By setting the boundaries of investigation, parsimonious models may provide good levels of predictive and explanatory power in relation to their focal phenomena and more impactful contributions [95].

As shown in Fig. 1, users' actions are conceptualized as three distinct constructs: perceived profile disclosure, active participation, and passive consumption. The extant literature posits that constructs are relevant and important in social capital formation [13, 44, 47, 94, 100]. Perceived profile disclosure is defined as the degree to which a P-SNS user perceives that personal and professional information is disclosed through the P-SNS's profile fields. These P-SNS profile fields may include information such as a photo, headline, summary, skills, location, contact, education, experience, etc. Active participation is defined as the degree to which P-SNS users generate content and react to others' posts. P-SNS users can actively participate in these sites by posting their opinions, updating their status, and sharing, commenting, and liking others' posts. Passive consumption is defined as the degree to which a user passively engages in a P-SNS (i.e., consumes content). Passive consumption includes, but not limited to, reading others' posts and newsfeeds.

Social capital sources are conceptualized as network size and social connectedness. Network size is defined as the number of direct connections a user has in a P-SNS. According to Lin [56], a larger network may be an indicator of a heterogeneous network that may help provide different and better resources than a smaller homogenous network. In their recent study, Shen & Gong [75] confirm that the network size in SNSs is positively associated with diversity. Therefore, network size, as a measure of network structure, can also be used as an approximation of diverse embedded resources (content) in larger networks.

While network size is an objective measure (number of first-level connections on LinkedIn) of social capital sources, a perceptual measure of social capital sources can be represented by social connectedness [47, 86]. Perceived social connectedness is defined as the degree to which a user in a P-SNS feels connected to others in the network. The extant literature on social capital supports the role of social connectedness in mediating the relationships between SNS use and different social capital outcomes [1, 32, 47, 98].

In the current investigation, perceived networking value is used to conceptualize the benefits people gain from their social networks as a result of networking activities. It is defined as the degree to which users perceive they can gain valuable benefits from their connections in a P-SNS [47, 90, 91]. These benefits, according to Lin [55, 56], are information, influence, social credentials, and reinforcement. The remainder of this section details the specific hypotheses, with their support from the extant literature.

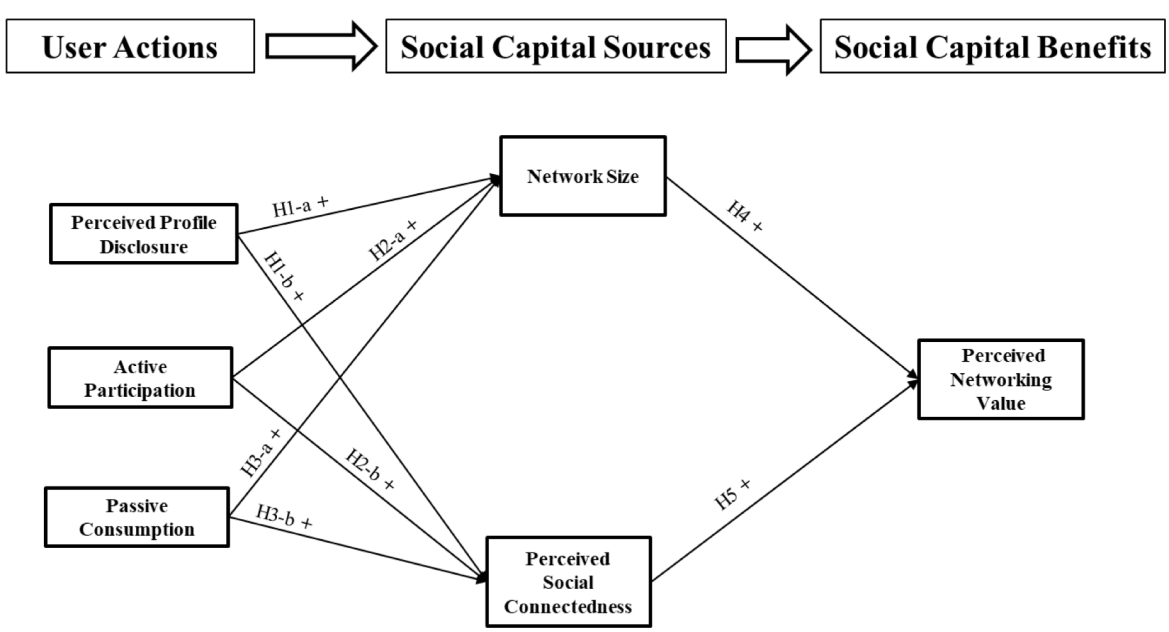

Fig. 1. Proposed research model for developing social capital through using P-SNSs.

4.1. Perceived profile disclosure

In this study, perceived profile disclosure aims to measure individuals' own evaluation of how much and how clearly they disclose their personal and professional information through the profile fields of their P-SNS account. It includes both the depth and breadth of information disclosed by users as well as how easy it is to find their skills and competencies. Self-disclosure, or intentionally revealing personal information to others, is a primary means of building relationships within SNSs [89]. When users disclose more information through their profiles, shared interests are more likely to be found with others in their immediate or extended networks. Therefore, establishing this common ground with others in the network through profile self-disclosure can result in more connections (network size) and access to more diverse resources [27]. Thus, the following hypothesis is posited as follows:

H1a. : Perceived profile disclosure in a P-SNS is positively associated with online network size.

Similarly, it can be argued that profile disclosure can be positively associated with perceived social connectedness. Perceived social connectedness is the "feeling of belongingness and affiliation that emerge from interpersonal relationships within social networks" ([33], p.1). It is about the quality and meaning of one's connections [77]. Since one's P-SNS profile plays a central role in the social capital formation process [40], and it is always visible to a user's network, engaged P-SNS users may place more effort in updating their profiles. P-SNS users also have the opportunity to compare their profile with their online peers, which may encourage them to further update/improve their own. Additionally, it has been shown that the interaction between self-disclosure and engagement is reciprocal and reinforced by sources of social capital such as social connectedness [50, 85]. Specifically, Utz [89] found that the feeling of connection as a relational outcome is fostered by private and public disclosures on SNSs. Thus, the following hypothesis is posited as follows:

H1b. : Perceived profile disclosure in a P-SNS is positively associated with perceived social connectedness.

4.2. Active participation and passive consumption

In addition to disclosing personal and professional information on P-SNSs, individuals typically perform various activities on these sites, including sharing updates and opinions, reading and following the news of their connections, commenting under others' posts, and reacting to others' posts ([13], 2010; [47]). Active participation and passive consumption in SNSs, specifically in P-SNSs, can increase individuals' network size, allow them to connect with more diverse and high-status people, and increase their engagement on these sites as they feel more connected to their network. As previously discussed, SNS users can establish different types of ties, such as interactions (e.g., sending messages and commenting under posts) and flows (e.g., posting an update, sharing an article, and reading a post), without necessarily being in the same network. Network activities (such as posting updates and sharing thoughts and feelings) can help SNS users establish such types of ties with broader audiences (latent ties), which can help them to extend their networks (size) and facilitate relationship development with more diverse and high-status individuals. For example, P-SNS posts that are liked by a connection in one's network enable that connection's network to view the original post. This may encourage network expansion as the post is viewed by individuals outside of the original poster's network. Thus, the following hypothesis is posited as follows:

H2a. : Active participation in a P-SNS is positively associated with online network size.

Engaging in SNS network activities more frequently can, similarly, increase perceived social connectedness [77]. S-SNS Facebook studies have found that active participation on this platform increases engagement and social connectedness [4, 47]. Similarly, Riedl et al., (2013) find that a high frequency of tweeting, as a measure of active participation on Twitter, predicts users' level of social connectedness. Thus, the following hypothesis is posited as follows:

H2b. : Active participation in a P-SNS is positively associated with perceived social connectedness.

Reading and following the news of connections also help SNS users to extend their networks (size). For example, when you read your connections' posts, you may request to add a latent tie that liked or commented on one of your connections' posts if you find common ground with this tie. Thus, the following hypothesis is posited as follows:

H3a. : Passive consumption in a P-SNS is positively associated with online network size.

Likewise, reading and following the news of connections in SNSs more frequently can enhance engagement and subsequently may increase perceived social connectedness [77]. A study on Facebook by Koroleva et al. [47] finds that passive following is positively associated with social connectedness. Thus, the following hypothesis is posited as follows:

H3b. : Passive consumption in a P-SNS is positively associated with perceived social connectedness.

4.3. Social capital sources and benefits

As people actively perform networking activities on P-SNSs by building their profiles and performing various activities as mentioned above, they create capacity or sources of social capital. Social capital sources, such as a large network size and high interconnectedness, can provide numerous benefits for SNSs users. To date, the majority of SNS studies have measured the benefits of social capital for SNS users under the two forms of social capital proposed by Putnam [71]: bridging and bonding social capital. However, SNS researchers tend to operationalize bridging and bonding social capital by using the scales developed by Williams [97], which were originally developed for general Internet users of chat rooms, email, and online video games [47]. As such, these scales may not be appropriate for measuring social capital benefits for SNS users due to the fact that there are technological differences between the general Internet and SNSs, which may result in distinct behavioral differences.[1] Additionally, most studies that have examined social capital benefits have focused on S-SNSs such as Facebook [101]. Since the motivations behind using S-SNSs and P-SNSs are different, users of such sites act differently, and, as a result, using the same scales for measuring social capital benefits may be inaccurate. Therefore, in this study, the focus is not on traditional bridging and bonding social capital. Instead, social capital benefits are operationalized as perceived networking value as most users of P-SNSs use such sites for networking purposes.

Examples of networking value in the context of P-SNSs include access to new information, obtaining professional advice, or claiming social credentials. The extant literature on the effect of network size on networking value has been mixed. Some have found that SNSs users can gain more networking value from their online social networks if they have a larger network size [14, 90]. They argue that SNSs can support larger networks of weaker ties due to the low cost of maintaining relationships in these sites. In addition, due to the visibility and association affordances of SNSs, it is easier to connect with latent ties, i.e., "friends of friends" in these sites [27]. Therefore, a larger network size in SNSs inevitably leads to more weak ties, which can increase one's access

[1] Unlike general Internet users, SNS users can publicly articulate their online social networks. This provides them with various possibilities to engage in social capital exchanges with other members in their networks such as the ability to "tag" others in an update which can be served as a form of social grooming behavior [49, 87].

to various resources such as new information and opportunities [75], and, as a result, more networking value. Meanwhile, others have found that the relationship between network size and bridging social capital is curvilinear [26]. Once a certain network size is reached, increasing one's network does not result in increased social capital benefits. While the extant literature is somewhat contradictory on the effects of network size, the preponderance of investigations indicates a positive association between network size and social capital benefits. As such, the following hypothesis is posited as follows:

H4. : P-SNS network size is positively associated with perceived networking value.

Similarly, a higher sense of connectivity within a P-SNS can lead to increased perceived networking value. A study by Koroleva et al. [47] finds that there is a significant positive association between social connectedness and networking value among Facebook users. In one of the few P-SNS studies, Utz (2016) finds that there is a positive association between network size and professional informational benefits reported by LinkedIn users. The extant literature on social connectedness also supports the association between social connectedness and various social capital outcomes [1, 32, 82]. Thus, the following hypothesis is posited as follows:

H5. : Perceived social connectedness in a P-SNSs is positively associated with perceived networking value.

5. Research methodology

5.1. The choice of research methodology

The underlying philosophical assumption of this research is grounded in a positivist paradigm in a deductive reasoning approach, as it draws from existing theories with pre-defined variables. Thus, a quantitative research methodology is well suited to address this study's research questions [62], where we emphasize precisely measuring variables and testing hypotheses that are linked to general causal explanation [65]. The current study utilizes an online survey to collect the required data for model validation. Surveys, specifically in the context of the IS discipline, are widely used and considered a common approach for data collection. They are very useful in answering different types of research questions including "why?", "how?", and "how many?". In addition, surveys, compared to other data collection techniques, are effective at reaching larger samples and are ideal for asking about user opinions and attitudes [64].

5.2. Data collection

The primary target population of this study was young and mid-aged adults (18–54 years old) who actively use LinkedIn. The main reason to target this age group is that, compared to other age groups, they are more likely to engage in networking activities such as self-promotion for professional purposes [78]. Being earlier in their professional careers, they are in the process of developing social capital as they seek to build and establish their professional networks. Thus, even small differences in their networking efforts on P-SNSs may lead to distinct differences among them in terms of perceived networking value. Participants were recruited from the target population at two major Canadian universities as well as through a market research firm. In total, 420 responses were collected for this study, of which 385 were usable. Thirty-five responses were omitted due to trivial responses, incompleteness, wrong answers to the quality questions, or duplicate responses. Table 1 highlights the demographic information of respondents.

Table 1
Demographic information.

Age	18–24	42.2%
	25–34	27.3%
	35–44	28.6%
	45–54	1.6%
	Prefer not to say/not applicable	0.3%
Gender	Female	62.6%
	Male	36.3%
	Other	0.8%
	Prefer not to say/not applicable	0.3%
Education	High school diploma	44.3%
	College diploma	8.8%
	Undergraduate bachelor's degree	25.7%
	Master's degree	16.4%
	Doctoral degree	4.5%
	Prefer not to say/not applicable	0.3%

5.3. Measurement

To ensure content validity, previously validated instruments were used in this study. Perceived profile disclosure was measured using Krasnova et al.'s (2010) profile disclosure scale; active participation and passive consumption were measured using Burke et al. [14] and Koroleva et al.'s [47] active participation and passive consumption scales; social connectedness was measured using Koroleva et al. [47] social connectedness scale, and networking value was built on Utz and Breuer's (2016) informational benefits scale and Koroleva et al.'s [47] networking value scale. As Utz and Breuer's (2016) informational benefits scale and Koroleva et al.'s [47] networking value scale only capture the information and influence dimensions of networking value, these scales are modified to capture other dimensions of networking value (social credentials and reinforcement) based on Lin's (2002, 2008) definition of social capital benefits. All items were measured on 7-point Likert scales. Social network size was measured using a single item, asking respondents to reveal their number of connections on LinkedIn.

6. Analysis and results

To validate the research model, structural equation modeling (SEM) was used. SEM combines a measurement model (i.e., confirmatory factor analysis) and a structural model (i.e., relationships between constructs of interest) [29]. PLS (a component-based SEM technique) is preferred over AMOS or LISREL (a covariance-based SEM technique) because PLS imposes minimum demands in terms of sample size, sample data distribution, and residuals distribution [19]. According to Hair et al. [34], the systematic evaluation of PLS-SEM results includes two stages: (1) evaluation of the measurement model and (2) evaluation of the structural model. SmartPLS 3 was used for our measurement and structural model evaluations.

6.1. Descriptive statistics

The dataset was examined for missing values, outliers, and non-normality using SPSS version 25. The number of missing values per indicator was less than 2 percent. Therefore, following Hair et al.'s (2016) recommendation, mean value replacement was applied instead of case-wise deletion to treat the missing values. Univariate outliers were identified and removed (6 cases) using z-test (z-scores with extreme absolute values greater than the critical value of 3.29). Multivariate outliers were identified using the Mahalanobis distance approach [61]. Applying a chi-square test ($p<0.001$, df=4) to four composite variables (i.e., perceived profile disclosure, active participation, passive consumption, and social connectedness), two cases appeared to have chi-square statistics higher than the critical value of 18.467 and were thus eliminated from the study. As a result, the number of cases was reduced to 377. The descriptive statistics of the measurement items used in this study are provided in Table 2. Although the PLS analysis method does not require normal distribution for data, the non-normality of data regarding skewness and kurtosis is not a severe issue. Regarding

Table 2
Descriptive statistics.

	Missing	Mean	Median	Min	Max	Standard deviation	Kurtosis	Skewness
Pro_Dis_1	0	4.814	5.000	1	7	1.450	−0.060	−0.690
Pro_Dis_2	0	4.769	5.000	1	7	1.443	−0.086	−0.671
Pro_Dis_3	0	4.836	5.000	1	7	1.393	0.165	−0.726
Pro_Dis_4	0	5.233	5.000	1	7	1.329	1.114	−1.062
S_Netw	0	3.568	3.000	1	9	2.721	−0.658	0.838
Soc_Con_1	0	4.095	4.000	1	7	1.593	−0.894	−0.157
Soc_Con_2	0	4.358	5.000	1	7	1.530	−0.636	−0.394
Soc_Con_3	0	4.745	5.000	1	7	1.451	−0.256	−0.617
Soc_Con_4	0	4.204	4.000	1	7	1.575	−0.844	−0.173
Soc_Con_5	0	4.143	4.000	1	7	1.601	−0.853	−0.161
Soc_Con_6	0	3.952	4.000	1	7	1.598	−0.862	0.051
A_Partici_1	0	2.300	1.500	1	7	1.599	0.824	1.321
A_Partici_2	0	2.261	1.500	1	7	1.541	1.205	1.398
A_Partici_3	0	3.387	3.000	1	7	1.858	−1.070	0.308
P_Consum_1	0	3.666	3.000	1	7	1.851	−1.044	0.235
P_Consum_2	0	4.220	4.000	1	7	1.889	−1.114	−0.104
P_Consum_3	0	3.883	4.000	1	7	1.860	−1.150	0.037
V_Netw_1	0	5.164	5.000	1	7	1.505	0.524	−0.981
V_Netw_2	0	4.912	5.000	1	7	1.549	−0.016	−0.804
V_Netw_3	0	4.379	5.000	1	7	1.474	−0.173	−0.552
V_Netw_4	0	4.491	5.000	1	7	1.511	−0.033	−0.604
V_Netw_5	0	4.708	5.000	1	7	1.529	0.111	−0.746
V_Netw_6	0	5.080	5.000	1	7	1.240	1.151	−0.805

Abbreviations: A_Partici = active participation; P_Consum = passive consumption; Pro_Dis = perceived profile disclosure; S_Netw = network size; Soc_Con = perceived social connectedness; V_Netw = perceived networking value.

skewness and kurtosis, values should ideally be within −1 and +1. Most indicators are within this range with the exception of A_Partici_1, A_Partici_2, and Pro_Dis_4, all three P-Consum indicators, and V_Netw_6. These are not considered substantial departures from normality (according to [96]), and, as such, these indicators are retained.

6.2. Evaluation of the measurement model

Based on Hair et al.'s (2016) guideline, the validation of the measurement model includes Cronbach's alpha and composite reliability to evaluate internal consistency, individual indicator reliability, and average variance extracted (AVE) to evaluate convergent validity, cross-loadings, the Fornell-Larcker criterion, and the heterotrait-monotrait ratio (HTMT) of the correlations to assess discriminant validity. All constructs passed the threshold value of 0.6 for Cronbach's alpha and composite reliability [34]. Convergent validity was assessed via items' outer loadings, indicators' reliability, and AVE. Except for V_Netw_1, all items passed the threshold value of 0.7 for outer loading, 0.5 for indicator's reliability, and 0.5 for AVE [34]. Regarding V_Netw_1 ("I receive information about job opportunities from my LinkedIn connections/groups"), in line with the guideline proposed by Hair et al. [34], this item was retained for two reasons: first, removing this item does not lead to an increase to composite reliability, and second, it is believed that removal of this item weakens the content validity of the associated construct (networking value). Finally, the measurement model was tested in terms of discriminant validity. Tables 3 to 6 show the results of items' cross-loadings, Fornell-Larcker criterion, convergent validity (outer loadings, indicator reliability, and AVE), and HTMT. As observed from the tables, each indicator's outer loading on its associated construct is greater than its loadings on other constructs (Table 3). In addition, the square root of each construct's AVE is greater than its highest correlation with any other construct (Table 4), and the AVE of all constructs is greater than 0.5 (Table 5). The final and most critical assessment of discriminant validity is HTMT as it has been shown to more accurately detect a lack of discriminant validity in variance-based SEM [37]. Considering the various criterion and statistical test approaches, Henseler et al. [37] conclude that the 0.85 criterion approach is the most conservative and best at detecting discriminant validity problems. As shown in Table 6, all HTMT values are lower than the threshold value of 0.85, providing confidence that the

Table 3
Discriminant validity results (cross-loadings).

	A_Partici	P_Consum	Pro_Disc	Soc_Con	Val_Netw
A_Partici_1	**0.936**	0.544	0.350	0.550	0.477
A_Partici_2	**0.908**	0.500	0.351	0.540	0.486
A_Partici_3	**0.861**	0.744	0.393	0.497	0.547
P_Consum_1	0.644	**0.933**	0.338	0.574	0.550
P_Consum_2	0.588	**0.941**	0.327	0.433	0.519
P_Consum_3	0.622	**0.944**	0.309	0.499	0.531
Pro_Dis_1	0.376	0.313	**0.916**	0.409	0.444
Pro_Dis_2	0.385	0.330	**0.926**	0.443	0.440
Pro_Dis_3	0.382	0.306	**0.914**	0.454	0.445
Pro_Dis_4	0.323	0.309	**0.875**	0.399	0.388
Soc_Con_1	0.465	0.381	0.381	**0.831**	0.523
Soc_Con_2	0.497	0.505	0.406	**0.874**	0.621
Soc_Con_3	0.413	0.455	0.472	**0.777**	0.545
Soc_Con_4	0.541	0.484	0.408	**0.917**	0.574
Soc_Con_5	0.560	0.495	0.399	**0.912**	0.573
Soc_Con_6	0.578	0.484	0.388	**0.901**	0.559
V_Netw_1	0.312	0.374	0.359	0.326	**0.689**
V_Netw_2	0.384	0.437	0.366	0.446	**0.737**
V_Netw_3	0.500	0.456	0.377	0.634	**0.821**
V_Netw_4	0.457	0.409	0.375	0.521	**0.810**
V_Netw_5	0.430	0.449	0.343	0.511	**0.804**
V_Netw_6	0.437	0.485	0.367	0.480	**0.723**

Abbreviations: A_Partici = active participation; P_Consum = passive consumption; Pro_Dis = perceived profile disclosure; Soc_Con = perceived social connectedness; V_Netw = perceived networking value.

Table 4
Discriminant validity results (Fornell-Larcker criterion).

	A_Partici	P_Consum	Pro_Disc	Soc_Con	Val_Netw
A_Partici	**0.902**				
P_Consum	0.660	**0.939**			
Pro_Disc	0.404	0.346	**0.908**		
Soc_Con	0.587	0.540	0.470	**0.870**	
Val_Netw	0.558	0.569	0.473	0.651	**0.766**

Table 5
Convergent validity results.

	Outer loadings > 0.7	Indicator reliability > 0.5	AVE > 0.5
A_Partici_1	0.936	0.876	0.814
A_Partici_2	0.908	0.824	
A_Partici_3	0.861	0.741	
P_Consum_1	0.933	0.870	0.882
P_Consum_2	0.941	0.885	
P_Consum_3	0.944	0.891	
Pro_Dis_1	0.916	0.839	0.825
Pro_Dis_2	0.926	0.857	
Pro_Dis_3	0.914	0.835	
Pro_Dis_4	0.875	0.766	
Soc_Con_1	0.831	0.691	0.757
Soc_Con_2	0.874	0.764	
Soc_Con_3	0.777	0.604	
Soc_Con_4	0.917	0.841	
Soc_Con_5	0.912	0.832	
Soc_Con_6	0.901	0.812	
V_Netw_1*	0.694	0.481	0.586
V_Netw_2	0.737	0.543	
V_Netw_3	0.821	0.674	
V_Netw_4	0.810	0.656	
V_Netw_5	0.804	0.646	
V_Netw_6	0.723	0.523	

Table 6
Discriminant validity results (HTMT).

	A_Partici	P_Consum	Pro_Disc	Soc_Con	Val_Netw
A_Partici					
P_Consum	0.725				
Pro_Disc	0.445	0.371			
Soc_Con	0.644	0.57	0.505		
Val_Netw	0.629	0.632	0.531	0.707	

constructs used in this study were distinct.

6.3. Evaluation of structural model

Based on Hair et al.'s (2016) guideline, evaluating a PLS-SEM structural model involves assessing the structural model for collinearity issues, coefficients of determination (R^2 values), and the size and the significance of the path coefficients. To assess collinearity, the following sets of predictor constructs are assessed: (1) active participation, passive consumption, and perceived profile disclosure as predictors of network size and perceived social connectedness; (2) network size and perceived social connectedness as predictors of perceived networking value. As shown in Table 7, all VIF values are clearly below the threshold of 5 [34]. Therefore, it can be concluded that collinearity among the predictor constructs is not a critical issue in the structural model.

Fig. 2 shows the results of R^2 values of endogenous variables. Following the Hair et al. [34] guideline, the R^2 value of Netw_S (0.240) can be considered weak, whereas the R^2 values of Soc_Con (0.474) and Val_Netw (0.459) are rather moderate. To determine the path coefficients and whether the relationships in the structural model are significant, the bootstrapping procedure was used. Using a bootstrapping procedure with 5000 samples, as shown in Fig. 2, all paths except for active participation → network size and network size → perceived networking value are significant.

There are four main findings from our results: (1) P-SNS users' actions (perceived profile disclosure, active participation, and passive consumption) have significant positive effects on perceived social connectedness (H1a, H1b, and H1c supported); (2) perceived social connectedness on P-SNSs has a significant positive effect on perceived networking value on these sites (H4 supported); (3) while perceived profile disclosure and passive consumption have significant positive effects on network size (H1b and H3b supported), active participation does not influence network size (H2b not supported); and (4) network size on P-SNSs does not have a significant effect on perceived networking value (H5 not supported). In sum, the more individuals perform various actions on P-SNSs, the more they perceive networking value if they feel connected to their networks on these sites. Also, while P-SNS users' actions such as profile disclosure and passive consumption can lead to increased network size, a larger network size does not necessarily lead to increased perceived networking value.

6.4. Common method bias

To assess the potential impact of common method bias in this research, a procedure proposed by Kock (2015) was followed. Through this procedure, we calculated variance inflation factors (VIFs) for all latent variables in the model. All VIF values are less than the recommended threshold of 3.3, indicating that common method bias did not impact this investigation.

7. Discussion

This research results show that active participation, followed by passive consumption and perceived profile disclosure, has significant positive effects on perceived social connectedness. These findings are supported by the extant literature [32, 46, 59] which indicates that individuals primarily engage with SNSs through active participation (e.g., like, comment, post/share, etc.) or passive consumption (e.g., follow the news of connections, look through their newsfeed, etc.) to maintain their relationships with others in their social networks [27, 91]. This leads to specific relational outcomes such as perceived relational closeness [12, 27, 47, 93]. Relational closeness can be enhanced as people continue engaging with SNSs [93]. An increased sense of relational closeness can eventually lead to enhancing the quality of relationships between individuals and their social network by creating feelings of connection or belongingness toward others in the network [63, 93]. This feeling of connection, according to Lin [56], is the outset layer of a social tie, which can serve as a basis for developing other layers of a social tie such as bonding [43].

This research also shows that while both active participation and passive consumption had very significant effects on perceived social connectedness ($p<0.001$), the path coefficient was higher for active participation. An individual's active participation in SNSs (through liking, commenting, or sharing others' posts) can be perceived as signal of attention. Gaining awareness and attention from others in a network strengthens reciprocal relationships and, as a result, creates a sense of connectivity [23, 27]. In contrast, passive consumption cannot create such an environment as it does not establish reciprocity [3]. Therefore, although still significant, the effect of passive consumption on perceived social connectedness may be more limited to the extent to which it can create relational closeness between a user and its network, as described earlier.

Based on the results of this research, perceived profile disclosure also positively affects perceived social connectedness. Users' perceived profile disclosure on SNSs is dependent on them disclosing personal and professional information through profile fields of their account. Increasing the depth and breadth of information shared via SNS profile fields can positively affect perceived social connectedness toward one's network in two ways. First, network members become more trusting of each other as they can establish more common grounds with each other. This enhanced trust, in turn, can facilitate relationship development and increase the feeling of connection among network members [83]. This can help explain why YouTube users tend to report lower levels of social connectedness than Facebook users. Profile features in YouTube, compared to Facebook, are limited and may not be sufficient for establishing trust and social connectedness [3].

Second, disclosing more personal and professional information on SNSs may increase users' engagement with these sites (e.g., spending

Table 7
Collinearity assessment of the structural model (VIF).

	A_Partici	Netw_S	P_Consum	Pro_Disc	Soc_Con	Val_Netw
A_Partici		2.040			2.040	
Netw_S						1.192
P_Consum		1.844			1.844	
Pro_Disc		1.344			1.344	
Soc_Con						1.072
Val_Netw						

Abbreviations: A_Partici = active participation; P_Consum = passive consumption; Pro_Dis = perceived profile disclosure; Soc_Con = perceived social connectedness; Val_Netw = perceived networking value.

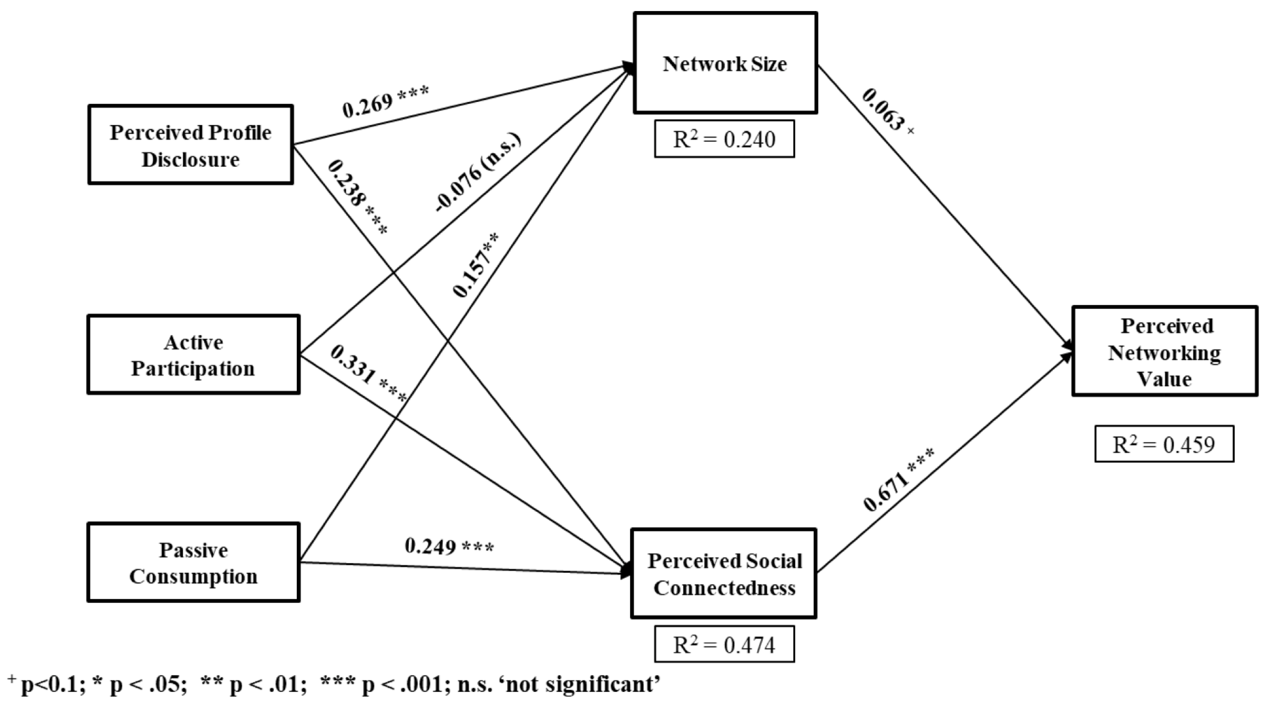

Fig. 2. Path coefficients and significance levels in the structural model.

more time/effort in enhancing one's profile) and may result in increased interactions with other members (e.g., asking for recommendations, endorsing skills, etc.) [3]. However, SNS users do not update their profile information or ask for recommendations/endorsements as frequently as they actively participate (like, comment, or share a post) or passively consume (follow or read newsfeed) on these sites [27]. SNS users that wish to enhance their social connectedness should be mindful to reflect updates in their profiles in addition to other active and passive SNS activities since all these user actions are significantly linked to feelings of social connectedness.

This study found that perceived social connectedness on P-SNSs has a significant positive effect on perceived networking value on these sites. This is in line with the extant literature that supports the association between social connectedness and various social capital outcomes such as networking value, life satisfaction, etc. [1, 32, 47, 82]. Social connectedness represents one's overall perception of the quality of relationships with one's network. As a source of social capital, individuals' social connectedness to their network indicates the amount of support they feel that they can obtain from their network. This feeling can lead to the formation of deeper social ties and feelings of bonding with a network [56]. Even if individuals possess valuable resources in their networks, without a sense of connectedness, they are less likely to mobilize such resources and gain benefits from them. This, in turn, may lead to decreased engagement with these sites.

This research shows that while perceived profile disclosure and passive consumption have significant positive effects on network size, active participation does not. It may seem surprising that one's active participation on SNSs does not affect one's network size because it is expected that the more SNS users actively engage in their online networks, the more they can expand their networks. To understand why this is not the case in this study, we need to understand how active participation may lead to an increased network size on SNS platforms. Active participation, as conceptualized in this study, includes three main actions: liking others' posts; commenting on others' posts; or sharing/resharing posts on one's wall. In general, if one's active participation on an SNS is to lead to an increased network size, these actions must be seen by an extended network (connections of one's connections) resulting in connection requests from that extended network. From the three actions that define active participation, two of them (liking and commenting on others' posts) are not seen by extended networks. Users must share/reshare a post and receive likes and comments on that post in order to broaden visibility to an extended network. This visibility can then result in connection requests that can expand one's network. In our research sample, approximately 80 percent of participants share a post almost monthly while less than 8 percent share a post weekly. The latter figure for the general LinkedIn population is only 1 percent [67]. This helps to explain our results as sharing a post on P-SNSs is not a frequent action, and other types of active participation such as liking and commenting have no or little effect on network size.

The mechanism through which one's network size is expanded is different for passive consumption and profile disclosure. For passive consumption, SNS users read and follow others' posts, which may include posts from an extended network (given that they received likes and comments by one's connections). This may prompt the SNS user to send a connection request and, if accepted, result in a larger network size. In our research sample, approximately 60 percent of participants read, follow, or click on the content shared by connections every 2–3 weeks. Thus, the frequency of passive consumption is higher than that of active participation. This may explain why, unlike active participation, passive consumption significantly affects network size.

The way individuals can add new people to their network through their profile disclosure is completely different than that of active participation and passive consumption. On LinkedIn, the "People You May Know" feature suggests other members for connection based on profile similarity factors. As such, the more users disclose their personal and professional information on LinkedIn, the more suggestions they receive, regardless of how much time they spend following other people on LinkedIn.

Our results show that network size on SNSs does not have a significant effect on perceived networking value. While our hypothesis was not supported, it is important to note that the extant literature on the effect of network size on social capital outcomes is contradictory. While some studies such as Burke et al. [14] and Utz (2016) found that network size positively affects bridging social capital on Facebook or professional informational benefits on LinkedIn, others found an inverted U-shape or no relationship between network size and social capital outcomes. For example, Ellison et al. [26] found that the number of actual friends (as a percentage of total number of Facebook friends) has a significant effect on bridging social capital, but the effect diminishes above the range of 400–500 [26]. In a similar vein, Tang and Lee (3013) found that network size on Facebook does not significantly affect offline and online political participation. Instead, the quality of a social network in terms of higher network heterogeneity may have an impact on social capital outcomes [84]. In subsequent research on the effects of networking on LinkedIn, Utz [91] found that only the total number of weak ties (not strong ties) is positively related to informational benefits [91].

In this research, the perceived networking value was conceptualized based on four social capital benefits proposed by Lin [56]: information; influence; social credential; and reinforcement. In a post hoc analysis, we separated the information dimension from the other three social capital benefits. Interestingly, we found that network size did have a significant positive impact on the information dimension of social capital benefits, more so than social connectedness. This suggests that network size may have an impact on limited facets of network value. Overall, our findings on network size emphasize the complex nature of this variable's effect of social capital outcomes, warranting further investigation.

8. Research contributions and limitations

This research on P-SNSs can be of interest and benefit to both academics in the discipline of IS as well as business practitioners. From a theoretical perspective, this research offers several contributions. First, P-SNSs, in general, are under-researched in IS. Therefore, by conducting this research on LinkedIn (one of the most widespread P-SNS platforms) and validating a model of social capital formation for the context of P-SNS, this research advances our knowledge of how individuals interact with these platforms. In addition to distinct differences in profile features on S-SNSs versus P-SNSs, these platforms differ in their nature of use which affects the social capital formation process. P-SNS users tend to have professionally driven motivations to engage on such sites rather than socializing with friends. Thus, expanding professional networks through self-promotion is a focus for P-SNSs users. This is even more important during a pandemic where traditional face-to-face networking is restricted and is expected to continue in a post-pandemic era where there will be more emphasis on working from home and online professional networking [17, 22].

Second, while past studies (e.g., [25]) have investigated the relationships between S-SNS users' specific activities and traditional bridging and bonding social capital, this research investigates the process (actions → social capital sources → social capital outcomes) by which actual social capital benefits are formed. Specifically, this study highlights the role of social capital sources. As such, this study helps to enhance the depth and breadth of our understanding of how social capital is formed in SNSs. To the best of our knowledge, this is the first study in the SNS context that investigated the role of one's profile in the social capital formation process, along with users' actions such as active participation and passive consumption. Thus, this study provides the opportunity to analyze the relative importance of each of these constructs in this process.

Third, as the use of P-SNSs for networking purposes has become widespread among professionals,[2] the perception of gaining actual value from these sites becomes increasingly important. As with any information technology, predicting outcomes (networking value) are important to understanding how to efficiently and effectively use such technology (P-SNSs). By measuring perceived networking value as we defined it (job leads, social credentials, referrals, and recognition), this research helps us improve the efficiency and effectiveness of the social capital formation process on these sites. This becomes even more important in pandemic and post-pandemic eras as there will be increased emphasis and reliance on online networking and the perceptions of networking value.

Fourth, the extant literature on the effect of network size on social capital outcomes is contradictory. We believe our findings on the relationship between network size and perceived networking value is an important step toward revealing the effect of network size on social capital outcomes.

This study targets different audiences interested in extending their networks, such as job seekers, recruiters, policymakers, and SNS providers. The results of this research can help these audiences to better understand the process of social capital formation and, as a result, assist them in playing a more effective role in this process. As such, from a practical perspective, this research offers several contributions. First, according to Utz [91], LinkedIn is widely used among professionals who engage in networking for various reasons. Additionally, senior students and fresh graduates can use P-SNSs to expand their social networks to help secure their first jobs. By understanding which factors significantly influence the social capital formation process on P-SNSs, this study can help such individuals to network more effectively and efficiently on these sites and, as a result, help them maximize the benefits they can gain from these sites. Second, as individuals place more emphasis on their online professional networking through P-SNSs, organizations can benefit from the enhanced profiles and activities of members by leveraging this rich data to find the best candidates to meet organizational goals. Third, the results of this study show that P-SNS platforms can potentially help people develop and accrue social capital more easily and at lower costs. As such, the results of this study can provide evidence for policymakers to emphasize the use of social media-based programs in federal and provincial employment services, such as career centers for the general public or welcome centers for new immigrants. Fourth, this research highlights the importance of one's profile and how it relates to specific benefits that P-SNS users can gain from these sites, such as social credentials and referrals. P-SNS providers can use the results of this study to help improve their networking services for their users. For example, from a design perspective, P-SNS providers can consider enhancing profile features to showcase social credentials of connections (which can enhance self-presentation affordances) and facilitating the referral process.

[2] LinkedIn, as the largest professionally oriented social network site, has around 310 million monthly active users [66]

Any empirical investigation has its own limitations that should be considered. First, as this research study is cross-sectional, a definitive causal relationship between independent and dependent variables cannot be drawn. For example, it is ultimately unclear whether an increased sense of connectivity in SNS users is formed because they disclose more information on their profiles, or they disclose more information on their profiles because they feel more connected to their social network. However, previous longitudinal studies in this domain support the causality relationship between actions and social capital benefits [12, 13, 80]. Second, using self-reported and perception measures rather than actual behavior is another limitation of this study. Although analyses showed that common method bias is not likely to be an issue in this investigation, it may be more accurate to use server data for measuring users' actions (active participation and passive consumption). However, it is important to note that LinkedIn has recently limited researchers' access to users' server data.

9. Conclusion

The main objective of this research was to propose and validate a model that explains the process by which individuals develop and accrue social capital through using P-SNSs such as LinkedIn. Survey results from 377 LinkedIn users revealed that (1) P-SNS users' actions (perceived profile disclosure, active participation, and passive consumption) have significant positive effects on perceived social connectedness; (2) perceived social connectedness on P-SNSs has a significant positive effect on perceived networking value on these sites; (3) perceived profile disclosure and passive consumption have significant positive effects on network size; (4) active participation does not have any effect on network size; and, finally, (5) network size on P-SNSs does not have a significant effect on perceived networking value.

While this research provides an important step in understanding the social capital formation process on P-SNSs, there are several interesting research questions that remain to be answered in this domain. One potential investigation is to use measures of network content such as network compositional quality along with network size (as a measure of network structure) to better understand the relative importance of network structure and content on the social capital formation process. Further, because of the importance of privacy settings in SNSs, it would be interesting to understand how users' choice of privacy settings affects the social capital formation process on these sites. Additionally, future work with longitudinal data could further our understanding of the directionality of key relationships in our research model.

CRediT author statement

Morteza Mashayekhi: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft

Milena Head: Supervision, Conceptualization, Writing - reviewing & editing, Funding acquisition

Appendix-1: Survey items

Construct*	Items
Perceived profile disclosure	**Pro_Dis_1 -** I have a comprehensive profile on LinkedIn.
	Pro_Dis_2 - I have a detailed profile on LinkedIn.
	Pro_Dis_3 - My profile tells a lot about me.
	Pro_Dis_4 - From my LinkedIn profile it would be easy to find out my skills and competencies.
Active participation	**A_Partici_1-** Commenting on posts
	A_Partici_2- Share something on your wall
	A_Partici_3- Like what connections post.
Passive consumption	**P_Consum_1-** Follow the news of your connections.
	P_Consum_2- Look through the newsfeed.
	P_Consum_3- Click on the content shared by connections.
Network size	How many first-level connections do you currently have on LinkedIn?
Perceived social connectedness	**Soc_Con_1-** Feel close to the people in my connection list.
	Soc_Con_2- Have a feeling of being connected to others.
	Soc_Con_3- I am updated about my connections.
	Soc_Con_4- Stay in touch with my connections.
	Soc_Con_5- Keep contact with the people in my connection list.
	Soc_Con_6- Interact with my connections more
Perceived networking value	**V_Netw_1-** I receive information about job opportunities from my LinkedIn connections/groups
	V_Netw_2- I get information about job market from my LinkedIn connections/groups
	V_Netw_3- Through my network connections on LinkedIn I can get easily valuable referrals.
	V_Netw_4- My LinkedIn connections elevate my social credentials in my field of work.
	V_Netw_5- Some of my LinkedIn connections/groups boost my identity and recognition.
	V_Netw_6- Information shared by my LinkedIn connections/groups is sufficiently timely.

* All construct items were measured on a 7-point Likert scale, with the exception of network size.

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