DEVELOPING SOCIAL CAPITAL THROUGH

PROFESSIONALLY-ORIENTED SOCIAL NETWORK SITES

# DEVELOPING SOCIAL CAPITAL THROUGH PROFESSIONALLY-ORIENTED SOCIAL NETWORK SITES

By

Morteza Mashayekhi, BSc., MSc., MBA

A Thesis

Submitted to the School of Graduate Studies

In Partial Fulfillment of the Requirements

for the Degree

Doctorate of Philosophy, Business Administration

McMaster University

McMaster University DOCTORATE OF PHILOSOPHY (2019) Hamilton, Ontario
(Business Administration - Information Systems)

TITLE: Developing Social Capital Through Professionally-Oriented Social Network Sites

AUTHOR: Morteza Mashayekhi, BSc., MSc., MBA

SUPERVISOR: Professor Milena Head

NUMBER OF PAGES: xiii, 182

## Lay Abstract

In recent years, people increasingly spend their time on various social network sites (SNSs) such as Facebook and LinkedIn. This raises a serious question as to how people gain actual benefits from using these sites. This research examines this question from the lens of social capital. As such, the main objective of this research was to propose and validate a model that explains the process by which individuals develop social capital through professionally-oriented SNS such as LinkedIn. This study finds that to gain actual benefits from professionally-oriented SNS, such as networking value, people need to feel connected to their social networks on the site. This feeling of connection requires that people actively participate on the site (e.g., share a post) rather than just reading and following other people's posts. Also, to connect with more people, individuals should disclose more information on the site.

## Abstract

Previous research has mainly focused on the social capital formation process on Facebook. In general, professionally-oriented social network sites (P-SNSs), such as LinkedIn, are under-researched in the Information Systems discipline. In addition, current studies do not include the effects of important elements of social network sites (SNS) 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 using P-SNSs. The theoretical framework of the proposed research draws upon Social Network Analysis, Social Media Analysis, and Social Capital Theory. Using an online survey of 377 LinkedIn users, this study finds 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, by including the profile disclosure construct in the research model, 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 such as active participation and passive consumption. From a practical perspective, this study has implications for different audiences such as job seekers, policy-makers, and P-SNS providers, assisting them in playing a more effective role in the social capital formation process on P-SNSs.



Keywords: social network sites, social capital, social network analysis, networking value, LinkedIn

## Acknowledgements

First and foremost, I would like to express sincere gratitude to my supervisor Dr. Milena Head for the continuous support of my Ph.D. study and research. Without her support, patience, and direction, this study would have never been completed. I could not have imagined having a better supervisor for my Ph.D. study.

Besides my supervisor, I was lucky enough to have two experienced supporting members in my supervisory committee: Dr. Brian Detlor and Dr. Khaled Hassanein. I would like to thank them for their insightful comments, encouragement, and support during these years.

Also, I want to thank Deb R. Baldry for her great support during these years.

Last but not least, I would like to thank my beloved wife, Fariba, who has always been there for me with her love, patience, and support.

This work is dedicated to my dad in heaven, Amir, and my mom, Tahereh, who always encouraged me to achieve the highest level of education; and to my wife, Fariba, who encouraged me to start my Ph.D. journey and supported me during these years.

## Table of Contents

# LIST OF TABLES AND FIGURES

## List of Tables

## List of Figures

# List of Abbreviations

| | |
|---|---|
| ANOVA | Analysis of Variance |
| AVE | Average Variance Extracted |
| CMV | Common Method Variance |
| IS | Information Systems |
| IT | Information Technology |
| MGA | Multi Group Analysis |
| PLS | Partial Least Squares |
| P-SNSs | Professionally-Oriented Social Network Sites |
| SCT | Social Capital Theory |
| SMA | Social Media Analysis |
| SNA | Social Network Analysis |
| SNSs | Social Network Sites |
| VIF | Variance Inflation Factor |

# Chapter 1 : Introduction

## 1.1 Research Problem and Objective

Social network sites (SNSs) such as Facebook, LinkedIn, and Twitter are a new class of information technologies that support interpersonal communication and collaboration using Internet-based platforms (Kane, Alavi, & Labianca, 2014). These sites differ in their primary purpose of use due to different platform features and design. For example, on Facebook, many profile fields are related to social aspects of life such as users' favorite films, music, and hobbies which make this platform an appropriate choice for socializing and maintaining relationships with friends. In contrast, on LinkedIn, profile fields resemble a resume, focusing more on professional networking, whereas on Twitter, profile fields are limited, as this platform is designed to facilitate the spread of news (Papacharissi, 2009). Therefore, SNSs are generally categorized as socially-oriented SNSs (S-SNSs) such as Facebook, professionally-oriented SNSs (P-SNSs) such as LinkedIn, and news and the event-following medium such as Twitter (Utz & Breuer, 2016).

In recent years, we have witnessed the rapid diffusion of SNSs. As of 2018, more than three billion people, around a quarter of world's population, actively use SNSs, spending on average 135 minutes per day on these sites (Globalwebindex, 2018; Statista.com, 2017). Interestingly, SNSs usage is not limited to younger adults anymore, as was the case in the early adoption of such sites. From 2011 to 2018, SNSs use by American adults ages 30-49 increased from 60% to 78%, while for those ages 50-65, the increase was from 37% to 64% and for those 65 and above, it was from 13% to 37% (Pew Research

Center, 2018). SNSs are also widely used among professionals. LinkedIn, as the world's largest P-SNS with more than 610 million members, now plays an important role in connecting professionals all around the world (LinkedIn.com, 2019; Zide, Elman, & Shahani-Denning, 2014).

It is, therefore, reasonable to say that 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 (Brandtzæg & Heim, 2009; Phua, Jin, & Kim, 2017; R. Smith, 2018). However, since the beginning of SNSs' wide adoption in 2003 (Boyd & Ellison, 2008), the question of whether and how people can gain tangible benefits from using these sites has drawn the attention of scholars, as well as policy makers.

To respond to this critical question, a stream of Information Systems (IS) research has tried to understand the benefits of using SNSs under the framework of social network and social capital theories (Ellison, 2007; Ellison, Vitak, & Gray, 2014; Steinfield, Ellison, Lampe, & J, 2013; M. Valenzuela & Sachdev, 2009). 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. Although early studies of SNSs showed a relationship between the use of SNSs and outcomes such as loneliness (Caplan, Williams, & Yee, 2009), later studies have differentiated between social activities and pure entertainment, finding that there is indeed a significant positive relationship between specific social activities such as network construction and content generation and social capital outcomes (Burke, Marlow, & Lento, 2010). However, the extant SNSs literature concerning social capital suffers from several gaps.

First, almost all SNS researchers focus on Facebook in their studies, which limits the depth and breadth of our understanding of how social capital forms in SNSs (Zhang & Leung, 2015). While it seems obvious that using P-SNSs, like LinkedIn, is more relevant to some aspects of social capital (e.g., resource exchanges) than using S-SNSs, like Facebook, surprisingly there are only a few studies that investigate the process of social capital formation on these sites. In general, P-SNSs are under-researched in IS (Blank & Lutz, 2016; Meng, Martinez, & Holmstrom, 2017; Zide et al., 2014).

Second, current studies do not include the effects of important elements of SNS, such as one's profile on social capital formation (Ellison & Vitak, 2015). This seems to be more relevant in P-SNSs than S-SNSs. Expanding one's professional network in the online world rather than socializing and maintaining relationships with friends is one of the primary goals for P-SNS users to engage in such sites. One's P-SNS profile is akin to an online resume, with richer affordances to attach elements such as video and audio. This profile plays a central role in fulfilling the goal of expanding one's professional network by establishing a common ground for professional self-promotion. Very limited studies have examined the impact of user profiles on these platforms (either S-SNS or P-SNS).

Third, while most studies mainly investigate the relationships between SNS use and bridging and bonding social capital, only a few studies have considered the role of social capital sources (Koroleva, Krasnova, Veltri, & Günther, 2011). Social capital sources lie in the structure and content of the social network and should be differentiated from social capital itself (Lin, 2008; Resnick, 2001; Tsai & Ghoshal, 1998). According to Lin (2008), social capital sources should be considered as necessary and important antecedents exogenous to social capital outcomes. However, the sources of social capital, such as a larger network size or social connectedness themselves are the outcomes of individuals' actions or investments in their social networks (Lin, 1999a, 2002b). As such, the role of social capital sources in social capital formation process should not be neglected (Koroleva et al., 2011)

Addressing these aforementioned gaps can increase the generalizability of social capital research in digital environments. As such, the overarching question of this research is "What is the process by which individuals develop and accrue social capital on P-SNSs?" Therefore, 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 using professionally-oriented SNSs (P-SNS), such as LinkedIn. More specifically, this study aims to answer the following research questions:

(1) How does user profile disclosure lead to accruing and developing social capital on P-SNSs?
(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?

## 1.2 Research Outline

The remainder of this thesis is organized as follows:

Chapter 2 provides a literature review on (1) definitions and conceptualizations of social media and social network sites (SNSs); and, (2) the extant social capital research in the online environment.

Chapter 3 provides a comprehensive discussion of the theoretical framework on which this research is built, and the proposed conceptual model resulted from the theoretical framework. Social Network Analysis, Social Media Analysis, and Social Capital Theory are three main foundational theories to be discussed. This chapter also proposes a research model that examines the antecedents of perceived networking value. Accordingly, relevant hypotheses are suggested.

In Chapter 4, the choice of research methodology, data collection procedure and operationalization of constructs, sample size requirements, measurement instrument design, and pilot test results are presented.

Chapter 5 describes the data analysis and research results. This chapter provides an evaluation of the measurement and structural model. The moderation role of control variables is examined, and the results of open-ended question analysis are presented.

Lastly, Chapter 6 provides a discussion on the answers to the research questions. Research contributions, limitations, future research suggestions, and a conclusion are outlined.

# Chapter 2 : Literature Review

In this chapter, first, definitions and conceptualizations of social media and social network sites are reviewed. Specifically, the definition the researcher adopted for the purpose of this research including two important aspects of that definition: user profiles and social media affordances is explained. Second, a review of the extant literature on social capital in an SNS context is presented. Last, due to the importance of the social connectedness concept in this research, the body of research in this area is reviewed.

## 2.1 Social Media and Social Network Sites (SNSs)

While various definitions of social media exist in the literature, most share three distinctive attributes: online communication, shared collaboration on generating content, and the ability to share this content with other people. For example, Safko and Brake (2009) defined social media as “activities among people gathered online who share information using conversational media that make it easy to create and share content in the form of words, pictures, videos, and audios” (Safko & Brake, 2009). Kaplan and Haenlein (2010) defined social media as “a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content” (p.61). Jones and Fox (2009) defined social media as “participative internet”. Kietsmann et al. (2011) defined social media by using seven functional building blocks: identity, conversations, sharing, presence, relationships, reputation, and groups (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011).

Kaplan et al. (2010) stress two key dimensions of social media which can differentiate social media from other media but also classify social media itself: (1) social presence, defined as acoustic, visual, and physical contact that can be achieved; and (2) self-presentation, defined as the process by which individuals attempt to control the impressions others have of them (Dominick, 1999; Kaplan & Haenlein, 2010). Social presence, which is directly associated with the capability of a media platform, can be expected to be higher for interpersonal (e.g., face-to-face discussion) than mediated (e.g., texting) and for synchronous (e.g., video chat) than asynchronous (e.g., e-mail) communications. According to social presence theory, the social influence that communication partners have on each other’s behaviour highly relies on their social presence (Kaplan & Haenlein, 2010; Short, Williams, & Christie, 1976).

According to Goffman (1959), people have the desire to control the impressions of other people toward themselves, and this desire affects their willingness to present or disclose themselves in any type of social interaction. The roots of this desire come from the fact that people try to influence others to gain rewards (e.g., make a positive impression to get a job) and create an image that is consistent with their personal identity (e.g., uploading a beautiful profile picture in Facebook to be perceived as young and attractive). One reason why people join Facebook is to present themselves in the online world. Self-presentation requires a certain amount of self-disclosure. For example, people on Facebook disclose some of their basic information to join this SNS and reveal their personal thoughts, feelings, likes, and dislikes that are consistent with the image they would like to show. Table 2.1 shows the classification of social media based on these two dimensions.

Table 2.1 Social Media Classification (Kaplan & Haenlein, 2010)

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="3">Social Presence</th></tr>
<tr><th>Low</th><th>Medium</th><th>High</th></tr>
<tr><td rowspan="2">Self-Presentation</td><td>High</td><td>Blog</td><td>Social networking sites (e.g., LinkedIn, Facebook)</td><td>Virtual social world (e.g., Second Life)</td></tr>
<tr><td>Low</td><td>Collaborative projects (e.g., Wikipedia)</td><td>Content communities (e.g., YouTube)</td><td>Virtual game world (e.g., World of Warcraft)</td></tr>
</table>

SNSs as a vibrant form of social media are widely used in a variety of different purposes specially for maintaining, strengthening, and developing social ties (Ellison & Vitak, 2015). Several terms and definitions have been used in the extant literature for SNSs (Adamic & Adar, 2005; Heidemann, Klier, & Probst, 2012). For example, Schneider et al. (2009) used the term online social networks (OSN) and defined it as ‘‘online communities among people with common interests, activities, backgrounds, and/or friendships. Most OSNs are Web-based and allow users to upload profiles (text, images, and videos) and interact with others in numerous ways’’ (Schneider, Feldmann, Krishnamurthy, & Willinger, 2009). Ellison and Boyd (2013) used the term social network site and defined it as “A networked communication platform in which participants 1) have uniquely identifiable profiles that consist of user-supplied content, content provided by other users, and/or system-level data; 2) can publicly articulate connections that can be viewed and traversed by others; and 3) can consume, produce, and/or interact with streams of user-generated content provided by their connections on the site” (Ellison & Boyd, 2013, p.7). This definition is particularly robust as it specifies two important aspects of SNSs (Ellison, Hancock, & Toma, 2012; Ellison & Vitak, 2015; Karahanna, Xu, Xu, & Zhang, 2018): (1) one's profile and (2) the affordances these platforms can provide such as enabling users to make their network of connections publicly visible and perform specific actions (consume, produce, and/or interact) on these sites. Therefore, this definition as a basis for the proposed research model is adopted. In the remainder of this section, these two aspects of SNSs: one's profile, and affordances are explained.

In the SNS context, one's profile plays an important role. It serves as the locus of interaction and represents the individual (Boyd, 2010). User profiles support relationship development because individuals through their profiles can communicate their identity information such as their hometown, current job, education and highlight their shared interests such as favourite songs, artists, hobbies. Sharing identity information and interests establishes common ground with other people so that people develop relationships more easily. Therefore, according to Ellison et al. (2015), one's profile can be used as "social lubricant, smoothing social interaction by highlighting commonalities and differences." Lampe et al. (2007) found that there is a significant association between completing some Facebook profile features and the number of friends one has on Facebook, suggesting that some profile features could help individuals to establish common ground with one another (Lampe, Ellison, & Steinfield, 2007). One's profile, specifically in P-SNSs, is a critical feature which can be effectively used for self-presentation purposes (Zide et al., 2014). For example, in LinkedIn, individuals can benefit from various profile features such as headline, summary, education, skills, experience, and recommendation to present themselves in their desired way (Damaschke, 2012).

Many definitions of social media and SNSs are either very narrow in scope, focusing on specific features (such as direct messaging, sharing content), or broadly differentiating such technologies from other traditional computer-mediated communication (CMC) technologies like e-mail (Treem & Leonardi, 2013). However, a more holistic approach to conceptualize social media and SNSs has emerged, known as an affordance-based approach (Boyd, 2010; Ellison & Vitak, 2015). The concept of affordance - broadly defined as possibilities for action (Evans, Pearce, Vitak, & Treem, 2017) - states that what an object affords not only depends on its physical properties, but also relies on the particular ways in which a user perceives and uses the object (Bucher & Helmond, 2016).

In the context of social media technologies, affordances of social media mean that the same SNS platform with specific features (e.g., LinkedIn) may be perceived differently in what it can afford for its users based on their differences in skills, intentions and actions and thus it may be used differently, resulting in different outcomes for them. However, affordances are not unlimited because they are associated with certain features of a technology. It is important to note that affordances are neither technology features (e.g., features in one's LinkedIn profile) nor an outcome (e.g., networking benefits). The affordance-based approach allows social media researchers to generalize their findings and relate them to higher-level characteristics of technology (such as visibility, editability) as opposed to the "idiosyncratic features of a particular technology or site" (Ellison & Vitak, 2015).

According to Treem et al. (2013), four affordances of social media are visibility, persistence, editability, and association. Visibility refers to providing the possibility for social media users to make information visible to others in a network. In a broader context, it refers to the means, methods, and opportunities for presentation (Bregman & Haythornthwaite, 2003). Persistence (also known as reviewability or recordability) refers to providing the possibility for social media users to have access to network content in its original format after it has been posted. Editability refers to providing the possibility for social media users to craft and recraft a posting before it is viewed by others as well as the ability to edit it after it has been posted. Finally, association refers to providing the possibility for social media users to both articulate connections between users (e.g., LinkedIn connections, Twitter followers), as well as the connections between users and the content they post (e.g., tagging a picture) (Ellison & Vitak, 2015; Treem & Leonardi, 2013).

A study by Karahanna et al. (2018) identified 12 main social media affordances for 21 major social media applications based on six types of social media categories identified by Kaplan and Haenlein (2010) (see Table 2.1). These affordances are: (1) self-presentation, (2) content sharing, (3) Interactivity, (4) Presence Signaling, (5) Relationship Formation, (6) Group Management, (7) Browsing Others' Content, (8) Meta-voicing, (9) Communication, (10) Collaboration, (11) Competition, and (12) Sourcing. The authors linked these affordances with specific features available on these applications and related them to user needs based on Self-Determination Theory (Deci and Ryan, 1985), and Psychological Ownership Theory (Pierce et al., 2001).

## 2.2 SNSs and Social Capital

This section aims to present a review of studies in SNSs with the focus on the extant literature on social capital. To fulfil this goal, first, different research streams in SNSs is reviewed in general and then the results of some studies that explain why people use such sites is highlighted. Finally, the SNS literature on social capital formation which is of primary interest in this study is reviewed.

A literature review by Berger et al. (2014) identified five main areas of research on SNSs in IS: (1) characteristics of SNSs; (2) users behaviour on SNSs; (3) privacy and SNSs; (4) SNSs in organizations and society; and (5) the design of SNSs (Berger, Klier, Klier, & Probst, 2014). Based on their literature review and subsequent work in this area (Liu, Ho, & Lu, 2017; Wehner, Ritter, & Leist, 2017), it can be understood that the research on characteristics of SNSs mainly focuses on SNS types or classes (Boyd & Ellison, 2008; Kaplan & Haenlein, 2010; Kietzmann et al., 2011; Quinio & Marciniak, 2013; Richter, Riemer, Brocke, & Grobe, 2009) as well as its effects, as a network of nodes and ties, on developing social relations (Krasnova, Koroleva, & Veltri, 2010; Schaefer, 2008), social capacity (Adams, 2011), social well-beings (Burke et al., 2010), social capital (Ellison, 2007; Ellison, Vitak, Gray, & Lampe, 2014; Lampe, 2015; Steinfield, Ellison, & Lampe, 2008), and diffusion of new products and brands (Brown, Broderick, & Lee, 2007; Kempe, Kleinberg, & Tardos, 2003; See-To & Ho, 2014).

Research on user behaviour mainly focuses on exploring user motivations to join SNSs (Alhabash & Ma, 2017; Bulut & Doğan, 2017; Krasnova, Hildebrand, Günther, & Kovrigin, 2008; Yin, Cheng, & Zhu, 2011), the effect of age, gender and other personal characteristics on SNS engagement (Chakraborty, Vishik, & Rao, 2013; Huang, 2019; Kim & Chock, 2017; Mehdizadeh, 2010; Skues, Williams, & Wise, 2012), and user tendency for information disclosure (Ashuri, Dvir-Gvisman, & Halperin, 2018; Brooks & Anene, 2012; R. Chen, 2013; Koohikamali, Peak, & Prybutok, 2017). Privacy issues in using SNSs is another important research stream that focuses on user privacy concerns such as the choices of privacy settings and personal information disclosure on these sites (Brooks & Anene, 2012; Krasnova, Veltri, & Günther, 2012; Ortiz, Chih, & Tsai, 2018; Stutzman, Capra, & Thompson, 2011; Tsay-Vogel, Shanahan, & Signorielli, 2018; Tufekci, 2008). Last, the applications of SNSs in organizations such as branding, health promotion, recruiting business professionals, and knowledge management (Gabarron, Årsand, & Wynn, 2018; Garg & Telang, 2012; Hagg, Dahinten, & Currie, 2018; Hemsley & Mason, 2013; Korda & Itani, 2013; Laroche, Habibi, & Richard, 2013; Shi, Poorisat, & Salmon, 2018), and SNS design requirements (Djonov & Van Leeuwen, 2018; Zagaar & Paul, 2012) have drawn the attention of IS scholars from around the globe in recent years.

A review of the scholarship on SNSs shows that about half of the research in SNSs was about Facebook (Meng et al., 2017). Also, among users of these sites, university and high school students were the major user population investigated (Meng et al., 2017; Zhang & Leung, 2015). A literature review by Zhang and Leung (2015) supports the thematic patterns of SNS research outlined by Boyd and Ellison (2007) that include impression management and friendship performance, network structure, bridging online and offline worlds, and privacy, however, it was found that the above four research patterns are not mutually exclusive. For example, studies on impression management and self-presentation also discussed information disclosure and privacy. They also found that Social Capital Theory is a popular theoretical framework among SNS researchers, however, very few studies (2.3%) actually discussed the effects of network features such as the density, diversity, and structural implication of SNS on social capital formation, suggesting that the research about the network structure in SNSs is still relatively under-developed (Zhang & Leung, 2015).

Recent research has explored why people use and continue to use SNSs. An emiprical study by Bulut et al. (2017) found that people use and continue to use SNSs for socializing, information seeking, communication, self-presentation, status seeking, entertainment, and business purposes (Bulut & Doğan, 2017). Whiting and Williams (2013) identified ten uses and gratification themes for using social media including social interaction, information seeking, passing time, entertainment, relaxation, expression of opinions, communicatory utility, convenience utility, information sharing and surveillance/knowledge about others. Social interaction and information seeking were found to be the most extensive motivations for people to use SNSs. Social interaction includes varous activities such as keeping in touch with family and friends, interacting with people that we do not regularly see, chatting with old acquaintances, and meeting new friends (Whiting & Williams, 2013). This aligns with previous research where it was found that people use SNS primarily for maintaining existing contacts, sharing and seeking information, communicating, forming new relationships and finally having fun (Brandtzæg & Heim, 2009; Schaefer, 2008). Based on the extant literature, Nadkarni and Hofmann

(2012) classify motivations to use social media into two braod groups: (1) the need to belong and (2) the need for self-presentation.

Research on how Internet use influences people's abilities to form and maintain social capital has been quite extensive (going back to Rheingold, 1993), but also contradictory (Ellison, N. , Lampe, C., Steinfield, C., & Vitak, 2011). While some research found that Internet use enables people to generate new social capital (Hampton & Wellman, 2003; Tiwari, Lane, & Alam, 2019; Zúñiga, Barnidge, & Scherman, 2017), others found that Internet use diminishes people's stock of social capital (Nie, 2001; Siraj, 2018). In recent years as the use of Internet-based communication technologies such as SNSs becomes widespread and people spend a large amount of time on SNS for socialization and networking (Globalwebindex, 2018; Statista.com, 2018), the question of whether and how people can gain tangible benefits from using these sites in their offline world has become critical and has gained a growing interest among a wide range of scholars and professionals in diverse disciplines and practical arenas (Ellison & Vitak, 2015; Mäntymäki & Islam, 2016; Zhang & Leung, 2015). In order to respond to this critical question, a stream of IS research has tried to understand the benefits of using SNSs under the framework of Social Capital Theory and Social Network Analysis (Ellison, N. , Lampe, C., Steinfield, C., & Vitak, 2011; Ellison, Steinfield, & Lampe, 2006; Ellison, Vitak, & Gray, 2014; S. Valenzuela, Park, & Kee, 2009). Table 2.2 provides a summary of some of these recent studies.

Table 2.2 A Summary of Recent Studies on Social Capital in SNS Context

| No. | Author(s) and Title | Independent Variable(s) | Dependent Variable(s) | Main Findings |
|---|---|---|---|---|
| 1 | **(Utz & Breuer, 2019)** The Relationship Between Networking, LinkedIn Use, and Retrieving Informational Benefits | Networking, weak ties, latent ties, strong ties, LinkedIn use, and professional content | Informational benefits | The study found that those who do networking are more likely to use LinkedIn. Networking is positively associated with active and passive use as well as the number of strong and latent ties on LinkedIn. Also, networking and several weak ties positively predicted informational benefits. The results indicate that networking on LinkedIn is a major driver of informational benefits. |
| 2 | (Tiwari et al., 2019) Do social networking sites build and maintain social capital online in rural communities? | SNS use (Facebook, Twitter, LinkedIn, and Instagram) | Bridging and bonding social capital | The study found that there is a significant positive association between SNS use in rural communities and bonding and bridging online social capital. Also, higher levels of SNS use are more effective in building and maintaining bridging social capital than bonding social capital. |
| 3 | (J.-H. T. Linn, 2019) Strategic Social Grooming: Emergent Social Grooming Styles on Facebook, Social Capital, and Well-Being | Social grooming behaviour | Bridging and bonding social capital, social connectedness, and well-being | The study found that five social grooming styles: image managers, social butterflies, trend followers, maintainers, and lurkers are significantly associated with social capital and well-being. Lurkers receive the fewest social benefits, whereas Image managers receive the most. Social butterflies have considerable bridging social capital but the least bonding social capital. |
| 4 | **(Munzel, Galan, & Meyer-Waarden, 2018)** Getting By or Getting Ahead on Social Networking Sites? The Role of Social Capital in Happiness and Well-Being | Intimacy and network size | Well-being Mediators: bridging and bonding social capital | The study found that intimacy and network size positively affect well-being, through social capital. Also, bridging social capital rather than bonding social capital is associated with novel information and experiences. |
| 5 | **(Abeele et al., 2018)** Does Facebook Use Predict College Students' Social Capital? A Replication of Ellison, Steinfield, and Lampe's (2007) Study Using the Original and More Recent Measures of Facebook Use and Social Capital | FB intensity use, active and passive FB use | Bridging and bonding social capital (measured by original scales and alternative scales) | This study replicated Ellison et al.'s study (2007) with original and alternative measures of social capital and Facebook use. Like the original study, it found that Facebook intensity use positively predicts the original social capital measures. However, the relationship between FB intensity use and alternative structural measures of SC was weak for bridging and absent for bonding social capital. |

Table 2.2 (Continued) A Summary of Recent Studies on Social Capital in SNS Context

| No. | Author(s) and Title | Independent Variable(s) | Dependent Variable(s) | Main Findings |
|---|---|---|---|---|
| 6 | **(Nolan, Hendricks, Williamson, & Ferguson, 2018)**<br>Social networking sites (SNS) as a tool for midwives to enhance social capital for adolescent mothers | NA | NA | Using a qualitative method, the study found that SNS use by adolescent mothers is positively associated with social capital (information) and enhance adolescent mothers' feelings of connectedness. |
| 7 | **(Phua et al., 2017)**<br>Uses and gratifications of social networking sites for bridging and bonding social capital: A comparison of Facebook, Twitter, Instagram, and Snapchat | SNS use | Bridging and bonding social capital | The study found that Snapchat users had the highest bonding social capital, followed by Facebook, Instagram, and Twitter, whereas Twitter users had the highest bridging social capital, followed by Instagram, Facebook, and Snapchat. Also, the relationship between SNS use and online bridging and bonding social capital were moderated by SNS intensity, trust, tie strength, homophily, privacy concerns, and introversion. |
| 8 | **(Yuan & Fussell, 2017)**<br>A tale of two sites: Dual social network site use and social network development | SNS use (Facebook, and Renren/Cyworld) | Bridging and bonding social capital | Using a survey of 335 Chinese and Korean students in the U.S., authors found that both Facebook use and Renren/Cyworld use are positively associated with bridging and bonding social capital. Therefore, it is concluded that when given multiple choices of SNSs, the affordances of SNSs are sustained across cultures, networks, and sites. |
| 9 | **(Verduyn, Ybarra, Résibois, Jonides, & Kross, 2017)**<br>Do Social Network Sites Enhance or Undermine Subjective Well-Being? A Critical Review | Active and passive SNSs use | Subjective well-being | The study found that there is a negative association between passively using SNSs and subjective well-being and positive association between actively using SNSs and subjective wellbeing. Also, active usage of SNSs predicts well-being by stimulating feelings of social connectedness. |
| 10 | **(Lu & Hampton, 2017)**<br>Beyond the power of networks: Differentiating network structure from social media affordances for perceived social support | Facebook use, close ties, and overall network size | FB social support | The study found that there is a positive association between close ties, overall network size, and diversity and social support on Facebook. Also, Facebook status updates and private messaging are independently associated with perceived support. |

Table 2.2 (Continued) A Summary of Recent Studies on Social Capital in SNS Context

| No. | Author(s) and Title | Independent Variable(s) | Dependent Variable(s) | Main Findings |
|---|---|---|---|---|
| 11 | (Zúñiga et al., 2017) Social Media Social Capital, Offline Social Capital, and Citizenship: Exploring Asymmetrical Social Capital Effects | Offline social capital, social media social capital | Online and offline political participation | The study found that social media social capital is empirically distinct from face-to-face social capital. Also, social media social capital tends to predict offline social capital more strongly than the other way around. Moreover, social media social capital influences people's participatory behaviours online and offline more so than offline social capital. |
| 12 | **(Chang, Liu, & Shen, 2017)** User trust in social networking services: A comparison of Facebook and LinkedIn | effort expectancy, social influence, privacy concerns, trust, perceived risk. | use behaviour | This study compares Facebook and LinkedIn to better understand factors affecting users' trust in SNS. Privacy concern influences perceived risks significantly stronger for Facebook instead of LinkedIn. |
| 13 | **(Utz & Breuer, 2016)** Informational benefits from social media use for professional purposes: Results from a longitudinal study | User activities, number of weak and strong ties, strategic networking | Professional informational benefits | Users of LinkedIn or other professional SNS consistently reported higher informational benefits than non-users. The number of ties on the SNS predicted informational benefits half a year later, and strong ties became more important over time. A reciprocal relationship between strategic networking and informational benefits was found. |
| 14 | **(Son, Lee, Cho, & Kim, 2016)** Examining online citizenship behaviours in social network sites: a social capital perspective | structural, relational, and cognitive dimensions of social capital | Citizenship behaviour | The study found that there is a significant positive association between the structural, relational, and cognitive dimensions of social capital and the SNS citizenship behaviour. Also, four key characteristics (exploration, communication support, playfulness, and responsiveness) of SNS affect the three dimensions of social capital. |
| 15 | **(Tian, 2016)** Network Domains in Social Networking Sites: Expectations, Meanings, and Social Capital | NA | NA | In a qualitative study, the author found that SNS users on homogeneous and closed networks (Renren) have different expectations than users on heterogeneous and open networks (Facebook) in terms of new information and support which led to developing different levels of bridging and bonding social capital in them. |

Table 2.2 (Continued) A Summary of Recent Studies on Social Capital in SNS Context

| No. | Author(s) and Title | Independent Variable(s) | Dependent Variable(s) | Main Findings |
|---|---|---|---|---|
| 15 | **(H. Chen & Beaudoin, 2016)** An empirical study of a social network site: Exploring the effects of social capital and information disclosure | social capital and information self-disclosure | viewer comments and favorites | The study using a content analysis of 558 photos on Flickr's Explore page found that social capital and self-disclosure indicators were positively associated with photo comments and photo favorites. |
| 16 | **(Ellison & Vitak, 2015)** Social Network Site Affordances and their Relationship to Social Capital Processes | NA | NA | In a conceptual study, authors provided an in-depth analysis of three main elements of SNSs including the profile, the public articulation of network, and generated content. They also explain social grooming practices on SNSs as specific relational behaviours that drive site use, enable resource-sharing, and aid relationship maintenance. |
| 17 | **(Utz, 2015a)** Is LinkedIn making you more successful? The informational benefits derived from public social media | Reading, posting, network size, strategic networking | Professional informational benefits | LinkedIn and Twitter users reported higher informational benefits than non-users, whereas Facebook users reported lower informational benefits. Posting and strategic networking predicted informational benefits. The network composition mattered most on LinkedIn; strong and weak ties predicted informational benefits. |
| 18 | **(Chiang & Suen, 2015)** Self-presentation and hiring recommendations in online communities: Lessons from LinkedIn | Self-presentation dimensions: argument quality and source credibility | Recruiter hiring recommendation | The study participants viewed potential candidates' LinkedIn profiles and responded to questions regarding the argument quality and source credibility of their self-presentations, fit perceptions, and hiring recommendations. The results show that recruiters make inferences about job seekers' person–job fit and person–organisation fit on the basis of argument quality in specific self-presentation categories, which in turn predict recruiters' intentions to recommend job seekers for hiring. |
| 19 | **(Zide et al., 2014)** LinkedIn and recruitment: how profiles differ across occupations. | LinkedIn profile fields | Hiring professional preferences | User unwillingness to fully complete the LinkedIn profile suggests that it may not have replaced the traditional resume yet. Sales/marketing professionals were more likely than HR and I/O psychology professionals to complete multiple aspects of a LinkedIn profile. Women were also less likely than men to provide personal information on their profiles. |

Table 2.2 (Continued) A Summary of Recent Studies on Social Capital in SNS Context

| No. | Author(s) and Title | Independent Variable(s) | Dependent Variable(s) | Main Findings |
|---|---|---|---|---|
| 20 | **(Burke & Kraut, 2014)** Growing Closer on Facebook: Changes in Tie Strength Through Social Network Site Use | Time spent on FB, direct communication, passive consumption, and broadcasting | Tie strength | Authors find that communication on the site is associated with changes in reported relationship closeness, over and above effects attributable to their face-to-face, phone, and email contact. Tie strength increases with both one-on-one communication, such as posts, comments, and messages, and through reading friends' broadcasted content, such as status updates and photos. The effect is greater for composed pieces, such as comments, posts, and messages than for "one-click" actions such as "likes." Facebook has a greater impact on non-family relationships and ties which do not frequently communicate via other channels. |
| 21 | (Ellison, Vitak, Gray, et al., 2014) Cultivating Social Resources on Social Network Sites: Facebook Relationship Maintenance Behaviours and Their Role in Social Capital Processes | demographic variables, time on site, total and "actual" Facebook Friends, and Facebook Relationship Maintenance Behaviours | bridging social capital (general and specific), Facebook Relationship Maintenance Behaviour (FRMB) | This study explores the relationship between perceived bridging social capital and specific Facebook-enabled communication behaviours. Total Facebook Friends significantly predicts bridging social capital; however, the impact of actual friends on general bridging social capital was stronger. There is a significant positive relationship between FRMB and bridging social capital. For Facebook users who report fewer actual friends on Facebook, greater engagement in FRMB was correlated with a larger increase in bridging social capital than for users who reported more actual friends on the site. |
| 22 | **(Seidman, 2013)** Self-presentation and belonging on Facebook: How personality influences social media use and motivations | Big Five: Extraversion, openness, agreeableness, neuroticism, conscientiousness | Communication, information seeking, presentation of self, connection/caring, self-disclosure | High agreeableness and neuroticism were the best predictors of belongingness-related behaviours and motivations. Extraversion was associated with more frequent use of Facebook to communicate with others. Self-presentational behaviours and motivations were best predicted by low conscientiousness and high neuroticism. Results suggest that conscientious individuals are cautious in their online self-presentation. Neuroticism, agreeableness, and extraversion were positively associated with the tendency to express one's actual self. |

Lin (1999a, 2008) defines social capital as investment in social relations by individuals. According to Lin (2008), individuals' instrumental or expressive actions let them have access to embedded resources in their social structure and reap the expected benefits. Instrumental actions are those actions taken by individuals to obtain resources not possessed by them such as economic, political, and social returns, whereas expressive actions are those actions taken by individuals to maintain resources they have already possessed such as physical health, mental health, and life satisfaction (Lin, 1999a). Lin (2008) argues that the extent to which individuals have access to resources embedded in their social network depends on the the locations in their network (structural-based factors), the value of individuals with whom a person has direct or indirect ties in terms of wealth, power, and status (resourse-based factors), and instrumental and expressive actions in their networks.

Putnam (2000) categorized social capital into two distinct forms: bridging social capital and bonding social capital. Bridging social capital is defined as having access to new and diverse information, which mainly depends on the strategic location of individuals in their networks (bridging location). In contrast, bonding social capital is defined as emotional and substantive support that individuals receive mainly from their close friends and family members (Ellison, Steinfield, & Lampe, 2007). These forms of social capitals were mainly conceptualized based on social network analysis theories, such as the strength of weak ties and structural holes theories (Burt, 2012; Granovetter, 1973). These theories are explained in more detail in the next chapter of this thesis.

Since the beginning of SNSs' wide adoption in 2003 (Boyd & Ellison, 2008), many studies has explored the extent to which SNSs can reinforce people's offline relationships and supplement social capital development (Burke, Kraut, & Marlow, 2011; Ellison, Steinfield, & Lampe, 2007a; Koroleva et al., 2011). These studies have mainly investigated the impact of general measures of SNS use (e.g., time on site, number of friends) or more recently specific kinds of activities that SNS users perform (e.g., generating content, social browsing) on important aspects of social capital such as informational and social support exchanges (Ellison & Vitak, 2015).

As one of the seminal works in this field, a study by Elisson et al. (2007) examined the relationship between Facebook use and bridging, bonding, and maintianed social capital among undergraduate students. The study found that while there is a strong relationship between Facebook use and all three forms of social capital, the effect is stronger on bridging social capital and among users experiencing low self-steem and low life satisfaction. However, due to the nature of the study (cross-sectional), the researchers could not conclude that in the relationship between Facebook use and social capital which precedes the other. To address this problem, a longitudinal study by Steinfield et al. (2008) provided evidence of a causal relationship between intensive Facebook use and bridging social capital. In addition, they argued that the high number of "friends" in Facebook should not be characterized as "ephemeral and shallow relationships" as it is in fact a characteristic of a large, heterogeneous network, necessary to support the formation of bridging social capital.

Replacing bridging and bonding social capital with some new measures of social capital such as students' life satisfaction, social trust, civic engagement, and political participation, Valenzuela et al. (2009) found that while there are positive relationships between the intensity of Facebook use and these measures of social capital, the size effects are small. Also, gender and education do not moderate the relationship between Facebook use and measures of social capital. Focusing on specific activities on Facebook such as directed communication and content consumption, Burke et al. (2010) found that: (1) directed communication is positively associated with bonding social capital; (2) surprisingly, the higher levels of content consumption is associated with decreased bridging and bonding social capital; (3) size of the network (number of friends) is correlated positively with bridging and bonding social capital and negatively with loneliness; and, (4) time spent on SNS (after controlling for the number of friends) is not a significant predictor of any measure of users' well-being (bridging and bonding social capital and loneliness).

Ellison et al. (2011) identified three communication patterns on Facebook including initiating a new relationship, maintaining an existing relationship, and information-seeking. Their research results showed that only a user's information-seeking behaviour significantly contributes to bridging and bonding social capital. They argued that the reason why initiating behaviour does not contribute to social capital benefits is that forming a new relationship is not the norm on Facebook. They also indicate that due to media multiplexity effects, close friends are probably more likely to make use of other channels of communication (e.g., face-to-face, phone, texting) to maintain their relationship than weak ties. Therefore, maintaining behaviour on Facebook may not contribute to social capital benefits. They also found that only those ‘friends’ who are considered ‘actual friends’ (actual friends is defined as those friends with whom a respondent has a strong tie) by participants are likely to provide social capital benefits. Moreover, they indicate that the relationship between the number of actual friends and bridging social capital is curvilinear, reaching a point where increases in the number of actual friends is no longer associated with higher social capital. They argued that the social and technical affordances of Facebook enable users to share their identity information and interests on this site which in turn establish common ground with latent ties (e.g., friends of friends), facilitating the process of converting latent ties to weak ties. Latent ties are defined as social ties that are “technically possible but not activated socially” (Donath & Boyd, 2004).

A longitudinal study by Burke et al. (2011) identified three distinct patterns of behaviour on Facebook including direct communication, generating content, and passive consumption. The research results showed that receiving messages from friends most contributes to bridging social capital. In addition, passively consume news by those with lower comfort in social interactions help them to improve modestly their bridge social capital. They argued that while Facebook is a network of ties, these ties do not directly equate to bridging social capital. In fact, for a tie to provide value, such as job information, a user must directly interact with that tie and ask for information.

Vitak et al. (2011) through re-examining the relationship between Facebook use and bonding social capital expanded the scope of bonding social capital by using categories of social provisions proposed by Robert S. Wiess (Weiss, 1974). They measured attachment (a sense of closeness and intimacy), reliable alliance (the availability of someone to provide tangible assistance), and guidance (whether an individual had social network members to turn to for advice) along with traditional bonding social capital. They found that Facebook is not associated with bonding social capital within a university setting. The research findings showed that while having a family member on Facebook significantly contributes to the perceived reliable alliance, reciprocity in communications is linked to perceived guidance. No evidence was found for supporting the relationship between different measures of Facebook use and attachment.

While almost all social capital studies in SNS context investigated the direct impacts of SNS use, specific users' behaviours, or some attributes of users' social network on social capital benefits, a study by Koroleva et al. (2011) provided a process-based model of social capital formation on SNSs that uncovered the mediating roles of two specific network attributes: (1) network structure; and (2) social connectedness on developing social capital benefits. In addition, the authors developed new scales for measuring social capital benefits, distancing themselves from traditional measures of social capital: bridging and bonding. They developed four new scales for measuring social capital benefits including networking value, horizon broadening, emotional support, and offline participation. Their research findings clearly support that network structure and social connectedness fully mediate the relationship between user actions (active participation and passive following) and networking value. In addition, network structure and social connectedness partially mediate the relationship between user actions (active participation and passive following) and horizon broadening. Moreover, their research results showed the relative importance of social connectedness on networking value, network structure on horizon broadening, active participation on emotional support, and social connectedness on offline participation.

A qualitative study by Vitak et al. (2012) found that while having access to a diverse network of individuals was noted as valuable by many participants, network composition in terms of multiple audiences within a network acted as a barrier to interaction. This kind of barrier in virtual social networks with diverse members is called “context collapse” which refers to the flattening of multiple audiences into one group (Boyd, 2008; Marwick & Boyd, 2011; Vitak & Ellison, 2013).

Distancing from the traditional measures of bridging and bonding social capital, a study by Zuniga et al. (2012) answered the question whether or not social capital derived from SNSs use can promote individuals to engage in public affairs or in their communities. The study found that news seeking behaviour on SNSs, after controlling for many demographic, socio-political factors as well as general SNS and media use, positively influence users’ social capital, civic engagement, and online and offline political participation (Zúñiga, Homero, Jung, & Valenzuela, 2012).

Lampe et al. (2013) found that older adults and those with higher perceived levels of bonding social capital are less likely to use Facebook. Privacy concerns, context collapse, and limited time are main reasons expressed by participants for not adopting Facebook. They also found that while there is no difference between light users and non-users in terms of reporting bridging social capital, heavy users reported higher perceived bridging and bonding social capital than either group.

In a seminal study by Steinfield et al. (2013), these authors outlined four broad areas of research on SNSs including: (1) impression management, (2) network structure, (3) bridging online and offline networks, and (4) privacy. They also identified three consistent themes across much of the social capital research in the SNS context including: (1) information disclosure on SNSs; (2) distinct forms of social capital benefits derived from SNS use; and (3) blending online and offline behaviour by SNSs use. Moreover, they suggested five areas for future research: (1) develop better measures of SNS usage; (2) improve measurement of social capital to measure actual benefits from social capital rather than the potential for future benefit; (3) using research methods that ascertain causal directions; (4) investigate other populations of users beyond students; and (5) research on social capital loss due to leaving an SNS (Steinfield et al., 2013).

Focusing on information seeking behaviour of SNS users, Sin and Kim (2013) found that younger students, undergraduates, and extroverts were more likely to use SNS for everyday life information seeking. Also, SNS usage emerged as the only positive predictor of perceived usefulness of acquired information in meeting daily needs, indicating that SNSs serve as a valuable channel for purposeful everyday life information seeking.

Combining server log analysis and longitudinal surveys of Facebook users, Burke & Kraut (2014) found that tie strength on Facebook increases with both direct communication, such as posts, comments, and messages, and passive consumption such as reading friends' status updates and photos. They also found that the effect of comments, posts, and messages on ties strength is stronger than that of "one-click" actions such as "likes". Using adults instead of students as target population, Ellison et al. (2014) found that Facebook use (minutes on Facebook), total and actual number of friends (actual friends is defined as those with whom a respondent has a strong tie), and maintaining behaviours of Facebook users significantly contribute to Facebook-specific and general bridging social capital. They also found that women and those with higher self-esteem reported higher perceived bridging social capital.

In a conceptual study, Ellison and Vitak (2015) focused on different affordances of social media and how these affordances enable new patterns of communications, interactions, and affiliations which may change individuals' network structure and content and as a result facilitate the development of social capital. They also provided an in-depth analysis of three main elements of SNSs including the profile, the public articulation of network, and generated content. They also explain social grooming practices on SNSs as specific relational behaviours that drive site use, enable resource-sharing, and aid relationship maintenance (Ellison & Vitak, 2015).

As one of the few studies on LinkedIn, Utz and Breuer (2016) examined whether and how the use of SNSs for professional purposes is related to informational benefits. In a longitudinal study, they found that: (1) LinkedIn users consistently reported higher informational benefits than non-users; (2) the network size on LinkedIn used for professional purposes predicted informational benefits half a year later, and strong ties became more important over time; and (3) while passive and active use of LinkedIn had positive concurrent effects on informational benefits, there was only very limited evidence for longitudinal effects of active and passive use of LinkedIn on informational benefits. Built on the definition of networking in the offline context by Wolff and Moser (2009), the authors also introduced the concept of strategic networking in the SNS context which refers to the strategic selection of ties on a SNS. They found some evidence for a reciprocal relationship between strategic networking and informational benefits (Utz & Breuer, 2016).

In a six-wave longitudinal study, Utz and Breuer (2017) found that there is a significant association between SNS use and online social support. However, higher levels of SNS use is also associated with higher levels of stress. In addition, SNS users and non-users did not differ in overall life satisfaction. Moreover, they found SNS users with lower life satisfaction and/or higher stress seek more social support online by asking for advice on SNS.

Comparing bridging and bonding social capital between different SNS platforms, Phua et al. (2017) found that Snapchat users had the highest bonding social capital, followed by Facebook, Instagram, and Twitter, whereas Twitter users had the highest bridging social capital, followed by Instagram, Facebook, and Snapchat. Also, the relationship between SNS use and online bridging and bonding social capital were moderated by SNS intensity, trust, tie strength, homophily, privacy concerns, and introversion.

A study by Munzel et al. (2018) on Facebook found that intimacy and network size positively affect well-being, through social capital. Also, the bridging social capital rather than bonding social capital is associated with novel information and experiences. The study found that those who do networking are more likely to use LinkedIn. Focusing on networking behaviour on LinkedIn, Utz and Breuer (2019) found that networking is positively associated with active and passive use as well as the number of strong and latent ties on LinkedIn. Also, networking and several weak ties positively predicted informational benefits. The results indicate that networking on LinkedIn is a major driver of informational benefits.

Due to the importance of the social connectedness concept in the social capital formation process, in the next section, some of the prominent studies that have investigated this concept are reviewed.

### 2.3 Social Connectedness

Social connectedness is one of the measures of belongingness proposed by Kohut's (1984) self psychology theory. It represents “cognitions of enduring interpersonal closeness with the social world in toto” (Lee, Draper, & Lee, 2001). It reflects how we assess the value of our social groups and perceive the meaningful connection with others above and beyond emotional feelings (Lee et al., 2001; Sinclair & Grieve, 2017). According to Grieve and Kemp (2015), perceived social connectedness is defined as the feelings of belongingness and affiliation that emerge from interpersonal relationships within social networks (Grieve & Kemp, 2015). According to Sinclair and Grieve (2017), while social connection, in general, can be measured by a total number of one’s connections or frequency of one’s participation in a social network, social connectedness measures the overall perception of quality and meaningfullness of one’s connections. It can also be interpreted as a measure of one’s aggregate relationships quality within a social network in terms of trust (Tsai & Ghoshal, 1998).

The extant literature supports the role of social connectedness derived from face-to-face social networking as a key determinant of various social capital outcomes such as less depression, higher subjective well-being, and higher self-esteem (Galloway & Henry, 2014; Jose, Ryan, & Pryor, 2012). However, little research has been done to date to examine whether, and if so, the extent to which social connectedness derived from an online world, specifically SNSs, can lead to similar results (Sinclair & Grieve, 2017). Table 2.3 summarizes recent studies on social connectedness in the SNS context.

Table 2.3 A Summary of recent Studies on Social Connectedness in SNS Context

| No. | Author(s) and Title | Independent Variable(s) | Dependent Variable(s) | Main Findings |
|---|---|---|---|---|
| 1 | **(Sinclair & Grieve, 2017)** Facebook as a source of social connectedness in older adults | No specific model | No specific model | Using factor analysis, the study found that social network on Facebook can be a source of social connectedness and that the social connectedness derived from Facebook is distinct but related to offline social connectedness. |
| 2 | **(Seabrook, Kern, & Rickard, 2016)** Social Networking Sites, Depression, and Anxiety: A Systematic Review | No specific model | No specific model | The systematic review found a positive association between social support and social connectedness and lower levels of depression and anxiety. |
| 3 | **(Praveena & Thomas, 2018)** Explaining user acceptance and usage of social networking sites: the role of trust, social connectedness, and visibility in extending UTAUT2 | UTAUT2 variables, trust, social connectedness, and visibility | Intention to use and usage | The study found that visibility is the main predictor of usage. Habit followed by social connectedness found to be the main predictors of behavioural intention. |
| 4 | **(Wu, Outley, Matarrita-Cascante, & Murphrey, 2016)** A Systematic Review of Recent Research on Adolescent Social Connectedness and Mental Health with Internet Technology Use | No specific model | No specific model | The results of the systematic review found that the use of Internet technology leads to an increased sense of connectedness to friends and school, while at the same time increasing levels of anxiety and loneliness among adolescents. |
| 5 | **(Grieve & Kemp, 2015)** Individual differences predicting social connectedness derived from Facebook: Some unexpected findings | Age, Gender, positive attitudes toward Facebook, extraversion and openness to experience | Social Connectedness (Facebook) | The study found that favourable attitudes to Facebook, extraversion, and openness to experience predicted Facebook social connectedness. Emotional stability is also positively associated with social connectedness. |
| 6 | **(Grieve, Indian, Witteveen, Tolan, & Marrington, 2013)** Face-to-face or Facebook: Can social connectedness be derived online? | Social connectedness | Depression, anxiety, and life satisfaction with life | The study found that Facebook use may provide social connectedness in the online environment, and that social connectedness derived from Facebook associated with lower depression and anxiety and greater satisfaction with life. |

Table 2.3 (continued) A Summary of recent Studies on Social Connectedness in SNS Context

| No. | Author(s) and Title | Independent Variable(s) | Dependent Variable(s) | Main Findings |
|---|---|---|---|---|
| 7 | **(Utz, 2015b)** The function of self-disclosure on social network sites: Not only intimate, but also positive and entertaining self-disclosures increase the feeling of connection | Disclosure measures | Social connectedness | The study found that positive and entertaining self-disclosures increased the feeling of connection, especially when reading friends' updates. |
| 8 | **(McIntyre, Wiener, & Saliba, 2015)** Compulsive Internet use and relations between social connectedness, and introversion | Introversion and compulsive Internet use (CIU) | Social connectedness | The study found that introverted individuals have more compulsive Internet use symptoms than extroverted individuals. Also, introversion and social connectedness was found to be negatively associated. In addition, individuals with more CIU had less social connectedness. |
| 9 | **(Riedl, Köbler, Goswami, & Krcmar, 2013)** Tweeting to Feel Connected: A Model for Social Connectedness in Online Social Networks | Social presence, social awareness, usage frequency and network size | Social connectedness | The study found that social awareness, social presence, and usage frequency have a direct effect on social connectedness, whereas network size has a moderating effect. |
| 10 | **(Allen, Ryan, Gray, McInerney, & Waters, 2014)** Social Media Use and Social Connectedness in Adolescents: The Positives and the Potential Pitfalls | No specific model | No specific model | The study found that SNSs can affect social connectedness in a paradoxical way. On one hand, they elevate social connectedness because they let individuals form and create online groups and communities, but on the other, they can create a source of alienation and ostracism. |
| 11 | **(Alloway, Horton, Alloway, & Dawson, 2013)** Social networking sites and cognitive abilities: Do they make you smarter? | Facebook use, YouTube use | Social connectedness, cognitive skills | The study found that the Facebook use is positively associated with social connectedness; however, there was no significant difference in reported levels of social connectedness between high and low YouTube users. |
| 12 | **(Ahn & Shin, 2013)** Is the social use of media for seeking connectedness or for avoiding social isolation? Mechanisms underlying media use and subjective well-being | SNS use, Face to face communication | Subjective Well-being | The study found that social connectedness mediates the effects of the social use of media on subjective well-being. Both connectedness and avoiding social isolation mediate the effects of face-to-face communication on subjective well-being. |

As one of the first few studies on social connectedness in the SNS context, Kobler et al. (2010) found that the more individuals actively disclose their information through status update messaging on Facebook, the more connected they feel on this platform. In addition, they found that individuals with higher social connectedness disclosed more diverse information on their profiles (e.g., location, feeling, activities, etc.) than those with lower social connectedness (Köbler, Riedl, Vetter, Leimeister, & Krcmar, 2010).

A study by Grieve et al. (2013) addressed two important research questions: (1) whether or not social connectedness derived from Facebook is a distinct construct separate from social connectedness experienced in a face-to-face social networking, and (2) whether or not there is a significant association between Facebook connectedness and anxiety, depression, and subjective wellbeing. The study found that Facebook connectedness is distinct from offline social connectedness. However, the feeling of disconnectedness from Facebook (for example, I feel like an outsider when I'm on Facebook) is more complex and may be attributed to both online and offline relationships. Also, the study found that Facebook connectedness is associated with lower depression and anxiety and greater satisfaction with life (Grieve et al., 2013).

In another study, Riedl et al. (2013) proposed a research model that explains the process through which social connectedness in SNS context is created. The study found that social presence on Twitter has a significant positive effect on social connectedness derived from this medium. Also, the frequency of use has a significant direct effect on social connectedness. Interestingly, they found that having a large network size on Twitter is not necessarily a determinant of feeling socially connected on this medium (Riedl et al., 2013).

A study on the role of individual differences on social connectedness derived from Facebook by Grieve and Kemp (2015) found that favourable attitudes to Facebook, extraversion, openness to experience, and emotional stability predict Facebook social connectedness. Interestingly, contrary to predominant view that SNSs is a purview of younger adults (Spies Shapiro & Margolin, 2014), they found no association between chronological age and Facebook social connectedness, suggesting that people of all ages may benefit from feelings of connectedness with other people on this medium (Grieve & Kemp, 2015).

To examine whether or not older adults similar to younger adults can derive feelings of connectedness from Facebook, Sinclair and Grieve (2017) examined older adults aged between 55 and 81 years and found that: (1) social network on Facebook can be a source of social connectedness for older adults; (2) the social connectedness derived from Facebook is distinct but related to offline social connectedness; and (3) older adults reported levels of Facebook social connectedness similar to those seen in younger samples in previous research (Sinclair & Grieve, 2017).

A study on functions of public self-disclosure on SNSs by Utz (2015) found that while there is a positive association between disclosure intimacy and feeling connected, positive and entertaining self-disclosures also increase the feeling of connection, especially when reading friends’ updates. According to Utz (2015), one interesting result of this study was that, while in face-to-face communications partner responsiveness plays an important role in building relational closeness, this may not be the case in online networking indicating that the results of dyadic face-to-face interactions may not be relevant on the SNS context (Utz, 2015b).

While the majority of studies on social connectedness were conducted on Facebook, a study by Stone and Logan (2018) examined the effect of social connectedness derived from WhatsApp among college students. The study found that the use of WhatsApp by students as an informal learning space leads to building a distinct sense of connectivity among these students. Building such a sense of connectivity, according to the authors, is not possible in an offline classroom (S. Stone & Logan, 2018).

## 2.4 Literature Review Conclusion

Reviewing research studies on the effects of SNS use on the social capital formation process and the role of social connectedness in this process reveals some important gaps in the extant literature that motivates this research:

- Professionally-oriented SNSs, such as LinkedIn, are under-researched. Most of the extant literature focuses on Facebook. Given the fact that more than 100 million people use at least one of P-SNS platforms (LinkedIn) on a daily basis (Apptopia.com, 2019), it is important to understand how users' actions on these sites can lead to actual benefits.
- Very little empirical research has been conducted to understand the role of online social network structure and content on the social capital formation process in SNSs.

Specifically, the role of social connectedness as a source of social capital in mediating the effects of SNS use on social capital outcomes is under-researched. Additionally, research findings on the effects of network size on social capital outcomes have been contradictory. While some studies found that network size positively affects bridging social capital, others found non-linear or no relationships between network size and bridging social capital. This calls for further investigation to clarify the nature of the relationship between network size and social capital outcomes using various SNS platforms, including P-SNSs.

- The extant literature lacks established scales for measuring constructs in an SNS context, such as profile completeness, users' actions, and social network related measures such as network structure, and social capital benefits.
- The current measures of social capital may not be as relevant in the context of SNS as they were originally developed for general Internet users (Williams 2006). Thus, measuring the unique and tangible benefits of SNSs may be difficult using these scales (Koroleva et al. 2011). This may be even more critical in P-SNSs than S-SNSs as P-SNS users tend to have professionally-driven motivations to engage on such sites rather than socializing with close friends. Therefore, P-SNS users expect to receive different types of value from such sites (e.g., networking value such as job leads, social credentials, referrals, recognition, etc.). Although Koroleva et al. (2011) proposed some new scales, these scales have not been tested to assess their reliability and validity in different contexts.

# Chapter 3 : Theoretical Background and Research Model

## 3.1 Theoretical Background

The main objective of this dissertation is to propose and validate a model that explains the process by which individuals develop and accrue social capital through the use of professionally-oriented social network sites (P-SNSs), such as LinkedIn. As such, the proposed research model draws upon the extant literature in social media (specifically social network sites), Social Network Analysis (SNA) (Burt, 2012; Granovetter, 1973, 1983), Social Media Analysis (SMA) (Kane et al., 2014), and Social Capital Theory (SCT) (Bourdieu, 1986; Coleman, 1988; Lin, 1992a, 1999a, 2002a; Lin, Cook, & Burt, 2001). While SNA helps us to understand how a social network structure can affect benefits that individuals can gain from their networks, SCT explains how embedded resources (e.g., status, wealth, power) and feelings of connectedness to a social network can affect those benefits. SMA provides a broader view on how individuals' different course of actions on P-SNSs and their personal differences can affect network structure and content.

### 3.1.1 Social Network Analysis

The debate over whether SNA is a theory of its own or is just a methodology persists in the extant literature (Borgatti & Halgin, 2011; Salancik & Burt, 1995). However, 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 rigorously provide a rich foundation for understanding the interaction processes and mechanisms that can yield certain outcomes for individuals and groups (Borgatti, SP., Mehra, A., Brass, D. J., & Labianca, 2009; Borgatti & Halgin, 2011; Burt, 2012; Granovetter, 1973). Although there are some small differences between these two theories, both theories are built on the same underlying model of how social networks work (Borgatti & Halgin, 2011) 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. Strength of a tie between two individuals is defined by a combination of the emotional intensity, amount of time, intimacy, and reciprocity between these two individuals. The stronger the tie between two individuals, the more likely they have common ties. A bridge is defined as a line in a network that provides the only path between two points and therefore, it provides the only route along which information or influence can flow from one point to another. Although weak ties are certainly not automatically bridges, all bridges are weak ties. Therefore, weak ties are a potential source of novel ideas, and as a result, individuals forming such ties can receive information that has not already circulated among their networks. SWT theory helps to explain why people may secure or at least hear about jobs through acquaintances rather than close friends because acquaintances as weak ties are potential sources of new information (Borgatti & Halgin, 2011; Granovetter, 1973).

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 structural holes. A structural hole is defined as a gap between two individuals. When an individual's network has more structural holes, he/she has more non-redundant ties and as a result has access to more novel information (Borgatti & Halgin, 2011; Burt, 2012). Both theories of SWT and SH share the same theoretical model of a social system where a network of paths acts as a channel for information to flow (network flow model). However, according to Borgatti et al. (2011), there are some network phenomena such as network organization and unionization which cannot fit the network flow model of the social system. Therefore, they proposed another model of a social system which they labeled as bond model (Borgatti & Halgin, 2011). The bond model of a social system is rooted in studies concerned with power (Cook & Emerson, 1978) and represents a social system as a group of ties bonded together. The bond model acts as a single entity with greater capabilities.

Borgatti et al. (2011) proposed a framework for theorizing SNA based on the underlying models of social systems discussed above and the generic types of outcomes that network research has sought to explain. Table 3.1 shows this proposed framework for theorizing SNA (Borgatti et al. 2011). According to Borgatti et al. (2011), there are two generic types of outcomes that SNA researchers have tried to explain: (1) individuals' choices which includes behaviours, attitudes, and beliefs, and (2) success, which includes performance and rewards. Combinations of models of social systems and outcomes can explain four types of phenomena in network research. However, as the goal of this study is to understand how an individual can gain actual benefits (success) from his/her own social networks in SNSs, the researcher is more interested in capitalization, the top left quadrant of the below table.

Table 3.1 Proposed framework for theorizing SNA (Borgatti & Halgin, 2011)

| | | Outcome | |
|---|---|---|---|
| | | **Success** | **Choice** |
| **Model of social system** | **Flow model** | Capitalization (social capital at the individual level) | Contagion (diffusion models) |
| | **Bond Model** | Cooperation (social capital at the collective level) | Convergence |

As shown in Table 3.1, social capital at the individual level consists of flow-based explanations of success. However, as explained in the following section of this thesis, the explanation of social capital based on the pure effects of social structure on outcomes is not complete. Social network theory ignores the attributes of individuals' contacts (e.g., how powerful or high status they are) and as a result, it should not solely be used to explain how people in a social network develop and accrue social capital (Borgatti & Halgin, 2011; Lin, 2008).

### 3.1.2 Social Capital Theory

According to Coleman (1988), social capital exists in the relations among people. Therefore, it is far less tangible than physical capital which exists in the form of observable material and human capital which exists in the form of the skills and knowledge acquired by a human. In addition, due to the complexity of social relations and various effects of social structures on those relations, social capital should be defined by its function rather than as a single entity. Social capital, according to Coleman (1988), is a concept that identifies the value of some aspects of social relations such as reciprocity, trustworthiness, information channels, norms and sanctions to individuals as resources they can use to achieve their interests. In addition, some aspects of social structure such as the closure of social networks facilitate certain actions of individuals in the social structure. Therefore, although social capital exists in different forms and entities, some aspects of social relations and social structures are common in them. Putnam (2000) defines social capital as "connections among individuals and the norms of reciprocity and trustworthiness that arise from them" (p.4). The core idea of SCT as Putnam (2000) stated is that social networks have value. Just like physical or human capital, social capital can increase the productivity of individuals and groups. In his 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 (Putnam, 2000).

Lin (1999a, 2008) defines social capital as investment in social relations by individuals through which they gain access to embedded resources in a social structure and mobilize such resources to enhance expected returns of instrumental or expressive actions. Three key elements in Lin's (2008) conceptualization of social capital are: (1) investment in social relations through individuals' instrumental or expressive actions; (2) access to embedded resources in a social structure by individuals and mobilize them; and (3) expected returns of actions (Lin, 1999a, 2008). According to Lin (1999a), people invest in social relations through their actions for instrumental and expressive purposes. Instrumental related actions are those actions taken by individuals to obtain resources not possessed by them such as economic, political, and social returns (e.g., networking to seek a new job), whereas expressive related actions are those actions taken by individuals to maintain or enhance resources they have already possessed such as physical health, mental health, and life satisfaction (Lin, 1999a).

According to Lin (2008), the effects of embedded resources on social capital development can be analyzed through: (1) network structure; and (2) network resources. Network structure analysis focuses on the pure effects of structure on expected returns of social capital. For example, the extent to which an individual's location in a social structure is close or far from a strategic location such as a bridge can affect the ability of that individual to access diverse and valued information. Other measures of location such as density, size, closeness, betweenness, and eigenvector can have different effects on individuals' accessibility to social resources in their networks. Network resource analysis focuses on the value of individuals with whom a person has direct or indirect ties in terms of wealth, power, and status (e.g., access to a person with high status in your network ) (Lin, 1981, 1992b). It is also important to note that in Lin's (1992b) conceptualization of social capital, accessing social capital is different from mobilizing social capital. Accessed social capital indicates the capacity of capital whereas mobilized social capital reflects the actual use of a particular social tie. For example, while having individuals with high status and power in one's network may indicate one's accessed social capital, using a particular contact (e.g., a manager, supervisor) in a job search process may indicate a mobilized social capital. However, the focus of most human and cultural theories is on measuring accessible capital rather than mobilized capital. Thus, the measurement of accessed social capital is usually preferred by researchers.

Researchers usually employ both types of analysis - network structure and network resources (content) - to develop appropriate measures of accessed social capital such as size (weak and strong ties), diversity or heterogeneity of resources, and composition of resources (Lin, 1999b). However, the large size of a network as an indicator of the heterogeneous network may not only reflect different and new resources, but also increases the chances of containing better resources (Lin, 2008). Therefore, in measuring accessed social capital for individuals with large network size, using the network size alone could provide a good approximation.

In addition to structure and resource dimensions of social capital, the pattern or quality of social relationships in a social network can mediate the relationship between actions (instrumental or expressive) and accessing and mobilizing social capital (Lin, 2008). According to Lin (2008), there are three layers of social relations within a network that vary in terms of intensity and reciprocity of relationships among ties. These three layers are binding, bonding, and belonging. The inner layer, called binding, is characterized by reciprocal and intimate relationships. The intermediary layer called bonding is characterized by shared information and resources, but they are not necessarily reciprocal. However, it increases the chance of keeping people connected in a social network. The belonging layer is the outer layer that is characterized by shared membership (e.g., members of a club or a professional group). Each outer layer can afford individuals within a social network to establish the inner layer of a relationship (Kawachi, Subramanian, & Kim, 2008). For example, one's feeling of connectivity or belongingness to a professional group increases the chance that he/she maintains his/her relationships with other members in that group, which in turn, promotes the reciprocal and intense interactions between his/her and other group members. This sense of connectivity is also known as social connectedness in the extant literature (Köbler et al., 2010; Sinclair & Grieve, 2017), and according to Koroleva (2011), represents "the qualitative source of social capital" (in contrast with quantitative measures of social capital such as network size). This dimension which is very close to what Ellison et al. (2007) proposed as "maintained social capital" captures one's sense of being in touch to his/her network. It can also be interpreted as a measure of one's aggregate relationships quality within a network in terms of trust (Tsai & Ghoshal, 1998).

It is important to note that social capital sources as conceptualized by Lin (2008) lie in the social network and should be differentiated from social capital itself (Lin, 2008; Resnick, 2001; Tsai & Ghoshal, 1998). According to Lin (2008), social capital sources should be considered as necessary and important antecedents exogenous to social capital outcomes. However, the sources of social capital such as a larger network size or increased social connectedness themselves are the outcomes of individuals' actions or investments in their social networks (Lin, 1999a, 2002b). Expected returns of social capital mainly depend on the purposes of actions as discussed above, and therefore may vary in their forms. However, in the context of this study, SNS users' networking activities on these sites can result in four specific benefits which may not be explained by other forms of capital such as human capital. These four benefits are (1) information, (2) influence, (3) social credentials, and (4) reinforcement. Regarding information, location of an individual in a social network in terms of how far or close he/she is to certain strategic locations and/or hierarchical positions in a network can provide him/her with useful information which otherwise is not available (Burt, 2012; Granovetter, 1973; Lin, 1999a). For example, a person located in a bridging location or close to a top manager (higher hierarchical position) may have better access to new information regarding a job opportunity than other individuals in that network.

Influence, another benefit of social capital, can be gained when an individual's social tie with more valued resources is able to affect the decision of a critical agent involving that individual. For example, an individual asks his/her connection (e.g., a well-known consultant) to exert his/her influence on a hiring decision. Social credentials are a type of benefit that an individual can gain in a social network due to his/her acknowledged connection to resources that are valuable for an organization because it reassures that organization that he/she can provide added resources beyond his/her personal capital (Lin, 1999a). For example, an individual's connection to a well-known expert in a high-tech industry can be considered a social credential for him/her because it may reassure others in a network that he/she can provide some benefits for them beyond his/her knowledge. Finally, being a part of a social network reinforces an individual's identity and recognition. It also serves as public acknowledgement of an individual's claim to certain resources (Lin, 1999a). For example, being connected to a number of highly recognized business consultants on LinkedIn or being a member of a well-known LinkedIn group (e.g., Certified

Business Consultants) may reinforce one's identity in his/her network and serves as a public acknowledgement of his/her claim to certain skills/knowledge.

Social Network Analysis (SNA) and Social Capital Theory (SCT) provide a theoretical framework under which people's actions within a social network (instrumental or expressive) can be linked to social capital sources (social structure, resources, and connectedness), and eventually to social capital outcomes or benefits (information, influence, social credentials, and reinforcement). In the next section, how SMA, proposed by Kane et al. (2014), addresses this theoretical framework in the online context, specifically in regard to a SNS context is explained.

### 3.1.3 Social Media Analysis

SMA, proposed by Kane et al. (2014), explains how content and structure of a social media network can affect its behaviour and shape its formation and characteristics. SMA is rooted in social network analysis (SNA) which has been a popular research stream for organizational studies in recent years (Kane, G. C., Alavi, M., Labianca, J., & Borgatti, 2014). SNA's focus and reliance on the network as its central construct as well as human social interactions make it well suited to support research in a social media context (Cross, Parker, & Borgatti, 2002; Kane, G. C., Alavi, M., Labianca, J., & Borgatti, 2014). SMA provides a rich set of concepts that help us understand how interactions of network-related structural and content factors and users' actions can result in different outcomes (Kane, G. C., Alavi, M., Labianca, J., & Borgatti, 2014).

A network's structure refers to "identifiable patterns of nodes and ties in a network" (Kane et al., 2014, p.3). Ties can be of different types, such as proximities (being in the same platform/group/location), social relations (friends, families, or affective relations), interactions (messaging, discussion boards), and flows (goods, information). The main difference between traditional SNA and SMA is that in SNA, the four types of ties are sequentially coupled with each other such that each serves as the foundation for the next (Atkin, 1977), whereas in SMA, these different ties on a platform are typically decoupled from one another. Therefore, in SMA, two nodes can have interactional ties with each other without necessarily having relational ties together. 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. However, there are some other structural factors which result from users' ability to accurately position themselves in a network which can lead them to have more access to new information such as degree centrality, closeness centrality, betweenness centrality, etc.

As such, structural factors can be categorized as either platform-driven factors or user-driven factors. On one side, platform-driven factors which result from the choice of platform design can shape and form the characteristics of a social media network. For example, relational ties design on Facebook ("friends") is different from that of Twitter ("followers") in that both parties in the relationship must confirm the tie on Facebook but not on Twitter. Thus, people in Facebook have greater control over the environment in which they network and as a result tend to have a more homogenized network. In contrast, the tie design in Twitter facilitates the flow of information toward more diverse people by making users' network less homogenized. On the other side, user-driven factors such as degree centrality, closeness centrality, and betweenness centrality which result from users' actions in their social network, can lead to very different outcomes for users (Kane et al., 2014). For example, connecting to more diverse people in LinkedIn puts individuals at a strategic location in their network which let them have more access to novel information.

A network's content refers to the resources available in the network (e.g., information, power, wealth, influence) (Borgatti & Foster, 2003). Content of a social media network is affected by its choice of platform design such as the forms of digital information that it can support like text, multimedia, and hypermedia, whether other members of the platform can contribute information to, edit, or create profiles for the user, and the degree to which the authenticity of users' profiles can be verified. However, there are some other network-related content factors which result from users' differences in the level of computer proficiency and choice of privacy settings which affect users' capability to have access to information (Gross & Acquisti, 2005).

Thus, platform-driven factors which result from the choice of platform design, can shape and form a social media network in a way that it becomes more homogenized, affecting the way information spreads across the network and influences users (Kane et al., 2014). For example, features of a LinkedIn profile enable users to disclose the same type of information and thus facilitates the searching and finding of people to connect. In contrast, user-driven factors, which result from users' differences in their actions to search and protect content within a social media network, can lead to different outcomes for social media users within a network. For example, changing the privacy setting of followers in LinkedIn from “everyone” to “your connections” can significantly affect individuals’ ability to see their second level of connections. Table 3.2 summarizes the SMA framework proposed by Kane et al. (2014)

Table 3.2 SMA framework proposed by Kane at al. (2014)

| | **Structure** | **Content** |
|---|---|---|
| **Platform** | Platform-driven factors: The characteristics of ties can be designed in a way that homogenize the network. (e.g., Facebook platforms enables an articulated list of ties, design of followers in Twitter and Friends on Facebook) | Platform-driven factors: The platform features regarding content can be designed in a way that homogenizes the network. (e.g., Features of LinkedIn profile enable users to disclose the same type of information, and thus facilitates searching and finding people to connect) |
| **User Actions** | User-driven factors: users’ different course of actions can lead to different outcomes in a network. (e.g., Higher betweenness centrality can result from users’ actions in a network leading to more access to information) | User-driven factors: users’ differences in their ability to search and protect content within a social media network can lead to different outcomes. (e.g., changing the privacy setting of followers in LinkedIn from “everyone” to “your connections” can significantly affect individuals’ ability to see their second level of connections) |

### 3.2 Proposed Conceptual Model

Figure 3.1 shows the proposed conceptual model which integrates the theoretical frameworks of Social Network Analysis, Social Media Analysis, and Social Capital Theory. As mentioned earlier, 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 using P-SNSs such as LinkedIn. P-SNSs offer various affordances for their users to fulfill their needs and motivations which are primarily networking and seeking professional information (Utz & Breuer, 2019). These affordances such as visibility, editability, persistence, and association (Boyd, 2010; Treem & Leonardi, 2013) enable users to perform various actions, such as disclosing their personal information through profile fields, active participation, and passive consumption in these sites. According to the Social Capital Theory proposed by Lin (1999a, 2008), individuals can gain various tangible benefits from their actions in their networks such as information, influence, social credentials, and reinforcement.

How individuals' actions in a network can lead to such benefits can be explained by a combination of SNA, SMA, and social capital theories and frameworks. The SMA framework proposed by Kane et al. (2014) explains how individuals' different course of actions on P-SNSs can affect network structure and content. The SNA theories, such as the strength of weak ties theory (Granovetter, 1973) and structural holes theory (Burt, 2012), explain the effects of social network structure on individuals' benefits. The SNA framework proposed by Borgatti et al. (2011) provides a bigger picture as to how models of a social network (the flow and bond model), in conjunction with individuals' performance and choices, can result in different consequences in a social network. Social Capital Theory (Coleman, 1988; Lin, 1992b, 1999a, 2002a, 2008; Putnam, 2000) and the extant literature on social capital explains how social structure, embedded resources within a social network as well as feelings of connectedness to a social network, known as social connectedness, can contribute to various social network benefits (Koroleva et al., 2011; Sinclair & Grieve, 2017; Tsai & Ghoshal, 1998; Utz & Breuer, 2016, 2019). It is important to note that only a part of the below conceptual model- the casual relationships between users' actions, social capital sources, and social capital benefits- will be empirically tested in this study mainly because: (1) it was not feasible to test all parts of the model in a single study; and (2) the selected part for the empirical study is core to answering the defined research questions.

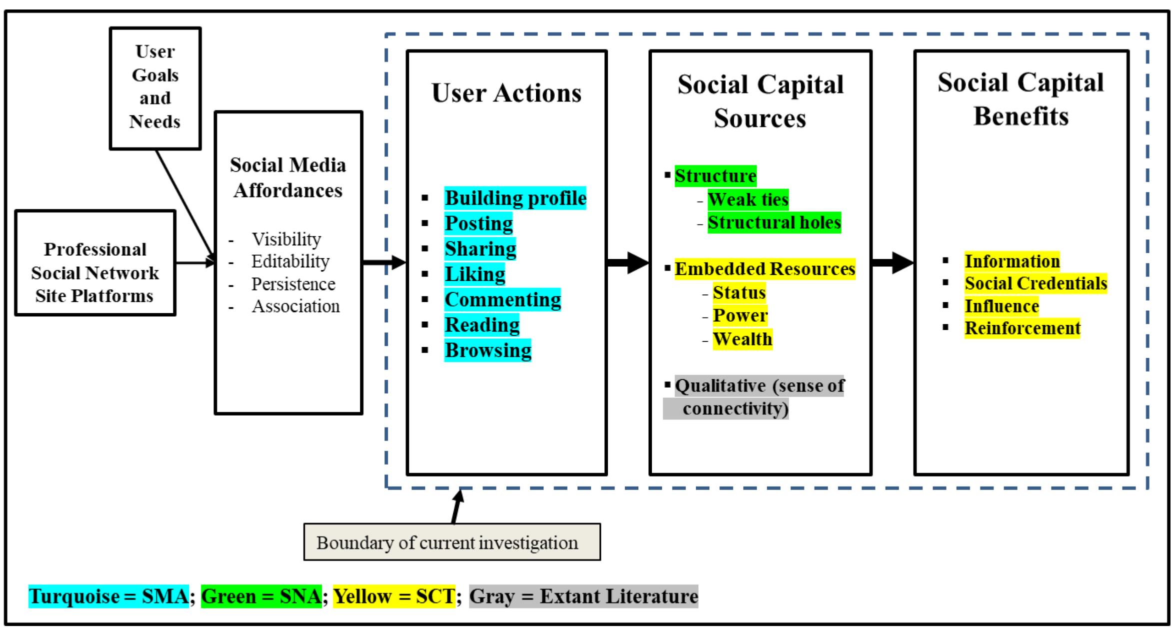



Figure 3.1 Conceptual framework for social capital formation in P-SNSs

### 3.3 Research Model and Hypotheses

Figure 3.2 shows the research model based on the conceptual framework discussed in the previous section. The core concept behind 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 (including network size, and social connectedness) which in turn will provide them valuable benefits (networking value). Table 3.3 provides a definition for each construct used in the research model.

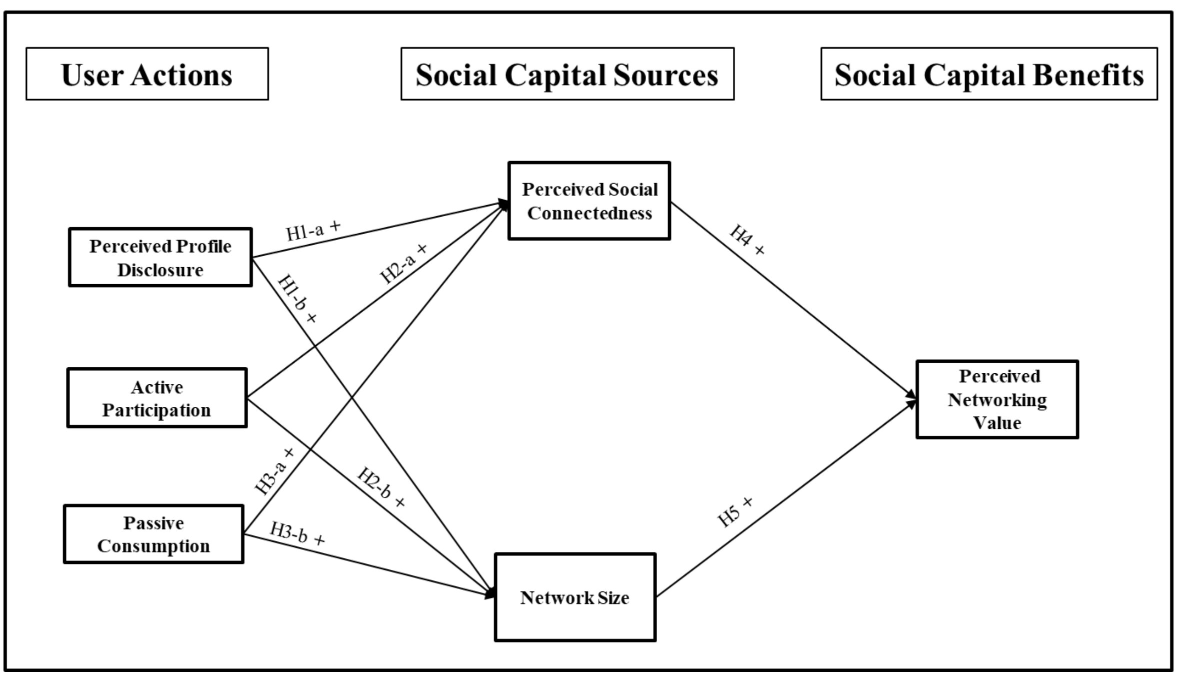



Figure 3.2 Proposed research model for developing social capital through using P-SNSs

Table 3.3 Definition of constructs used in this study

| Construct | Definition | Main Reference(s) |
|---|---|---|
| Perceived Profile Disclosure | The degree to which a P-SNS user perceives he/she discloses his/her personal and professional information through profile fields of his/her personal account. | Krasnova and Veltri's (2010) |
| Active Participation | The degree to which P-SNS users generate content and react to others' posts. | Burke et al. (2010)<br>Koroleva et al. (2011) |
| Passive Consumption | The degree to which a user passively engages in a P-SNS (i.e., consumes content). | Burke et al. (2010)<br>Koroleva et al. (2011) |
| Network Size/degree | The number of connections a user has in a P-SNS. | NA |
| Perceived Social Connectedness | The degree to which a user in a P-SNS feels connected to others in the P-SNS. | Koroleva et al. (2011) |
| Perceived Networking Value | The degree to which a user perceives he/she can get valuable benefits from his/her connections in a P-SNS. | Lin (1999)<br>Utz and Breuer's (2016)<br>Koroleva et al. (2011) |

As discussed earlier, SNSs through affording visibility, persistence, editability, and association enables people to perform various activities in the online world. Since people mainly use P-SNSs for networking (Zide et al., 2014), in a broader sense, it is reasonable to say that P-SNSs afford networking for their users. This is very much in line with what Zhang and Leung (2015) proposed to define "SNS" as "social networking service" instead of "social network site". Networking defined as "individuals' attempts to develop and maintain relationships with others who have the potential to assist them in their work or career" (Forret & Dougherty, 2001) is a conscious investment in social relations which can lead to developing and accruing social capital (Resnick, 2001).

In the physical world, networking encompasses several activities including creating a list of "Level 1" networking contacts such as friends, family, relatives, past and current colleagues, preparing a resume, attending networking events and presenting oneself, listening to what other people say to gather information, and conducting follow-ups. Likewise, in the online world, SNS affordances enable people to build their profile which functions the same as a resume (though with much more affordances such as adding an external video), actively construct their network by adding people, generate content to establish ties with broader audiences, directly communicate with other people through sending messages or commenting under their posts, and read what other people shared and posted to gather information. As such, people through networking in SNSs not only can build and develop their social network in the same way they do in the offline world, but also, they can do it more efficiently and effectively because affordances of SNSs enable people to cross the boundaries of time and location and maintain and forms relationships with wide range of contacts with minimum costs (Utz & Breuer, 2019).

As can be seen in Figure 3.2, users' actions are conceptualized as three distinct constructs: perceived profile disclosure, active participation, and passive consumption. These constructs are frequently used in the extant literature (Burke, Kraut, & Marlow, 2011; Khan, 2017; Koroleva et al., 2011; Wang, Gaskin, Rost, & Gentile, 2018; Yu, 2016). Perceived profile disclosure is defined as the degree to which a P-SNS user perceives he/she discloses his/her personal and professional information through profile fields of his/her personal account. P-SNS platforms such as LinkedIn provide different sections that enable users to disclose their personal and professional information such as 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 looking through their news-feed.

Social capital sources are conceptualized as network size and social connectedness. Network size is defined as the number of connections a user has in a p-SNS. Network size in this research represents social network structure and embedded resources (content). According to Lin (2008), a larger network may be an indicator of a heterogeneous network that reflects different and new resources as well as increased chances of containing better resources. Shen et al. (2019) found that the network size in SNSs is positively associated with diversity (Shen & Gong, 2019). Therefore, while network size can be used to measure network structure with any network size, it can also be used as a good approximation to measure both network structure and content for individuals with large network size. While network size can be interpreted as a quantitative measure of social capital sources, a qualitative measure of social capital sources can be represented by social connectedness (Koroleva et al., 2011; Tsai & Ghoshal, 1998). Perceived social connectedness is defined as the degree to which a user in a P-SNS feels connected to others in the P-SNS. Extant literature on social capital supports the role of social connectedness in mediating the relationships between SNS use and different social capital outcomes (Ahn & Shin, 2013;

Grieve et al., 2013; Koroleva et al., 2011; Wu et al., 2016). In this research, the perceived networking value is used to conceptualize the benefits people gain from their social networks as a result of networking activities and it is defined as the degree to which a user perceives he/she can gain valuable benefits from his/her connections in a P-SNS (Koroleva et al., 2011; Utz & Breuer, 2016, 2019). These benefits, according to Lin (2008), are information, influence, social credentials, and reinforcement.

The rest of the current section explains the hypotheses drawn upon the proposed research model.

### 3.3.1 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 profile fields of their P-SNS account. It includes both depth and breath of information disclosed by a user as well as how easy it is to find his/her skills and competencies. Disclosing more identity information and shared interests by individuals in their profiles can establish more common grounds with other people leading to forming more connections (size) and accessing more diverse resources (Ellison & Vitak, 2015). According to Krasnova (2010), the convenience of maintaining and developing relationships on SNSs is a primary motivation to disclose information on these sites. Lampe et al. (2007) found that there is a significant association between completing some Facebook profile features (such as hometown, high school, preferences information) and number of friends, suggesting that some profile features could help individuals to establish common ground with one another. According to Utz (2015), relationship development occurs primarily through self-disclosure, or intentionally revealing personal information to others. In addition, through various affordances of one's profile (e.g., linking videos, presentations, personal websites to one's profile) people can present themselves in their ideal way which may help them to more easily connect to more high-status people in their extended network. Previous researchers have found that the extent to which people felt their profile reflected their personal identity is positively associated with the amount of information they disclosed in users' Facebook profiles (Nie & Sundar, 2013). Lin et al. (2014) found that there is a significant association between network size and need for impression management (H. Linn, Tov, & Qiu, 2014).

Likewise, it can be argued that profile disclosure can be positively associated with perceived social connectedness. Perceived social connectedness can be viewed as the "feeling of belongingness and affiliation that emerge from interpersonal relationships within social networks" (Grieve & Kemp, 2015, p.1). Perceived social connectedness is about the quality and meaning of one's connections (Sinclair & Grieve, 2017). Since one's P-SNS profile plays a central role in the social capital formation process and the fact that it is always visible to a user's network, engaged P-SNS users may spend more time updating their profiles. Also, P-SNS users have the opportunity to compare their profile with their online peers and make appropriate periodic improvements. Therefore, it can be argued that profile disclosure in a P-SNS context requires a higher level of engagement than it does in S-SNSs, which may result in stronger feelings of connections. In addition, past research shows that in general the interaction between self-disclosure and engagement is reciprocal, and reinforced by sources of social capital such as social connectedness (Ledbetter, A. M., Mazer, J. P., DeGroot, J. M., Meyer, K. R., Mao, Y., & Swafford, 2011; Trepte & Behavior, 2013). A literature review by Abramova et al. (2017) shows that individuals' self-disclosure on SNSs can lead to relational outcomes. Utz (2015) found that the feeling of connection as a relational outcome reported by several SNS users can be fostered by private and public disclosures on these sites (Utz, 2015b). Thus, the following hypotheses are posited:

H1a: Perceived profile disclosure in a P-SNS is positively associated with perceived social connectedness.

H1b: Perceived profile disclosure in a P-SNS is positively associated with online network size.

### 3.3.2 Active Participation and Passive Consumption

In addition to disclosing personal and professional information on P-SNSs, people usually perform various activities on these sites which are central to their daily experiences such as posting an update, sharing their thoughts and feelings, reading and following the news of their connections, commenting under others' posts, and reacting to others' posts (Burke et al., 2011, 2010; Koroleva et al., 2011). 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 make them more engaged in these sites so that they feel more connected to their network. As discussed earlier, people in SNSs can establish different types of ties such as interactions (e.g., sending messages, commenting under posts) and flows (e.g., posting an update, sharing an article, reading a post) without necessarily being in the same network. Performing more network activities such as posting an update, sharing thoughts and feelings, reading and following others' posts, and commenting under others' posts help SNS users to establish such types of ties with broader audiences (latent ties) that help them to extend their networks (size) and facilitate relationship development with more diverse and high-status individuals. For example, once you post an update and it receives a 'like' from one of your connections, all connections of that specific connection can see your post and may request to add you to their networks. Conversely, when you read your connections' posts, you may request to add a latent tie that liked or commented on one of your connections' post if you find common ground with him/her. Likewise, performing such activities in SNSs more frequently can make individuals more engaged in their social networks and as a result, may increase their perceived social connectedness (Sinclair & Grieve, 2017). Ellison et al. (2007) find that Facebook intensity use is positively associated with the formation of social connectedness. A study on Facebook by Koroleva et al. (2011) finds that active participation and passive following significantly affects social connectedness. Similarly, Riedl et al. (2013) find that high frequency of tweeting, as a measure of active participation on Twitter, predicts users' level of social connectedness. Alloway et al. (2013) found that increased engagement on Facebook is related to higher levels of social connectedness. Thus, the following hypotheses are posited:

H2a: Active participation in a P-SNS is positively associated with perceived social connectedness.

H2b: Active participation in a P-SNS is positively associated with online network size.

H3a: Passive consumption in a P-SNS is positively associated with perceived social connectedness.

H3b: Passive consumption in a P-SNS is positively associated with online network size.

### 3.3.3 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 large network size and high interconnectedness can provide numerous benefits for SNSs users. Until now, the majority of SNS studies have measured the benefits of social capital for SNS users under two forms of social capital proposed by Putnam (2000): bridging and bonding social capital. However, most SNS researchers operationalize bridging and bonding social capital by using the scales developed by Williams (2006), which was originally developed for general internet users such as users of chat rooms, email, and online video games (Koroleva et al., 2011). As such, these scales are not 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 result in distinct behavioural patterns between the general Internet and SNS users[1]. In addition, most of these studies have measured the social capital benefits resulted from using socially-oriented SNSs such as Facebook (Zhang & Leung, 2015).

To date, only two studies have investigated social capital benefits resulting from using P-SNSs, such as LinkedIn: (1) Utz & Breuer (2016) and (2) Utz & Breuer (2019). The researcher believes that since the motivations behind using socially and professionally 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 is operationalized as perceived networking value mainly because most users of P-SNSs use such sites for networking purposes. Examples of networking values in the context of P-SNSs includes access to new information, getting professional advice, or claiming social credentials.

P-SNSs users can gain more networking value from their online social networks if they have larger network size. SNSs can support larger networks of weaker ties due to the low cost of maintaining relationships in these sites. In addition, due to visibility and association affordances of SNSs, it is easier to connect with latent ties, i.e., “friends of friends” in these sites. (Ellison & Vitak, 2015). Therefore, a larger network size in SNSs inevitably leads to more weak ties which increase one’s access to various resources such as new information and opportunities (Shen & Gong, 2019) and as a result more networking

[1] Unlike general Internet users, SNS users can publicly articulate their online social networks. This provides them 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 behaviour.

value. Similarly, a higher sense of connectivity within a social network by P-SNS users can lead to more perceived networking value. A study by Koroleva et al. (2011) finds that there is a significant positive association between social connectedness and networking value among Facebook users. 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 support the association between social connectedness and various social capital outcomes (Ahn & Shin, 2013; Grieve et al., 2013; S. Stone & Logan, 2018). Thus, the following hypotheses are posited:

H4: Perceived social connectedness in a P-SNSs is positively associated with perceived networking value.

H5: Online network size is positively associated with perceived networking value.

In this study, various control variables including gender, education, age, LinkedIn membership status, job seeking status, and immigration status will be examined to understand differences among survey participants and the potential effects of these differences on the social capital formation process.

# Chapter 4 : Research Methodology

This chapter outlines the research methodology used in this dissertation. The choice of research methodology, data collection procedure and operationalization of constructs, sample size requirements, measurement instrument design, pilot test, and data analysis method are presented in this chapter.

## 4.1 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 (Myers, 2013). However, as this research seeks to obtain an understanding of attitudes and motivations of SNS users, a qualitative research method is also employed in order to provide richer insights. Therefore, a combination of quantitative (survey) and qualitative (open-ended survey questions) approaches are used in order to answer the study's research questions (Myers, 2013; Venkatesh, Brown, & Bala, 2013).

The current study utilizes an online survey to collect the required data for model validation including constructs items, demographics, control variables, and open-ended questions. 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 less costly to reach larger samples, ideals for asking about opinions and attitudes, more accurate generalizability, and easy to administrate (Nardi, 2018; Pinsonneault & Kraemer, 1993; Webster & Trevino, 1995)

### 4.2 Data Collection

An online survey was designed to test the hypotheses posed by the proposed research model. The primary target population of this study was young and mid-aged adults (18-44 years old) who actively use LinkedIn. The main reason to target this age group is that they typically are in the process of developing social capital (E. J. Smith et al., 2015). Therefore, 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 Ryerson Universities and McMaster University as well as through Qualtrics, a research service firm.

The online survey included 27 questions followed by a single open-ended question. On average, it took participants about 20 minutes to complete the survey. Prior to answering the survey, participants were required to read and agree to a consent form describing the purpose of the research, the procedure involved, potential benefits and risks, confidentiality, withdrawal information, and researchers' contact information. A couple of tutorial pages were created to help participants answer questions related to their various profile feature settings on their LinkedIn accounts (See Appendix-1, 2, and 3 for consent form, survey questions, and tutorial pages respectively).

### 4.3 Sample Size Requirements

To determine the required sample size for this study, two approaches were used. First, according to Gefen et al. (2000), the minimum sample size required for validating the model in PLS should be at least ten times the number of items in the most complex construct (Gefen, Straub, & Boudreau, 2000). In this study, the most complex construct is perceived networking value or perceived social connectedness with six items. Therefore, a minimum sample size of 60 participants requires for this study.

The second approach, proposed by Cohen (1992), argues that the minimum number of participants depends on the sufficient statistical power and effect size for the relationships. Based on the literature in Information Systems and social capital, the minimum number of sample size required to achieve a sufficient statistical power of 0.8, a small effect size of 0.10, the significance level of 0.05, and with five predictors is 122 (Cohen, 1992; Roldán & Sánchez-Franco, 2012). This is also in line with Green's (1991) approximation for the minimum sample size. To account for response rate and possible spoiled surveys, 420 participants were targeted for this study.

### 4.4 Measurement Instrument

In order to ensure content validity previously validated instruments were used in this study. Table 4.1 shows the main references used for each scale used in this study along with the type of construct (formative or reflective), and the measurement method for each construct. Perceived profile disclosure was measured using Krasnova and Veltri's (2010) profile disclosure scale; active participation and passive consumption were measured using Burke et al. (2010) and Koroleva et al.'s (2011) active participation and passive consumption scales; social connectedness was measured using Koroleva et al. (2011) social connectedness scale, and networking value were built on Utz and Breuer's (2016) informational benefits scale and Koroleva et al.'s (2011) networking value scale. As Utz and Breuer's (2016) informational benefits scale and Koroleva et al.'s (2011) 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 (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.

The decision concerning construct type - reflective or formative - is made based on the following criteria (Hair, Hult, Ringle, & Sarstedt, 2016): (1) causal priority between the indicator and the construct (Diamantopoulos & Winklhofer, 2001), (2) whether the construct is a trait explaining the indicators or rather a combination of the indicators (Fornell & Bookstein, 1982), (3) whether the indicators represent consequences or causes of the construct (Rossiter, 2002), (4) whether the items are mutually interchangeable or not (Jarvis, MacKenzie, & Podsakoff, 2003). Table 4.2 shows the measurement items for constructs used in this study.

Table 4.1 Main references for scales used in this study

| Construct Name | Construct Type | Measurement method | Main Reference(s) |
|---|---|---|---|
| Perceived Profile Disclosure | Reflective | 7-point Likert scale: Disagree strongly (1) – Agree strongly (7) | Krasnova and Veltri's (2010) |
| Active Participation | Reflective | 7-point Likert scale: almost never (1) -almost everyday (7) | Burke et al. (2010) Koroleva et al. (2011) |
| Passive Consumption | Reflective | 7-point Likert scale: almost never (1) -almost everyday (7) | Burke et al. (2010) Koroleva et al. (2011) |
| Network Size/degree | NA | An individual item for measuring the size of the network (Categorical measurement) | NA |
| Perceived Social Connectedness | Reflective | 7-point Likert scale: Disagree strongly (1) – Agree strongly (7) | Koroleva et al. (2011) |
| Perceived Networking Value | Reflective | 7-point Likert scale: Disagree strongly (1) – Agree strongly (7) | Lin (1999) Utz and Breuer's (2016) Koroleva et al. (2011) |

Table 4.2 Measurement Items for Constructs

| Construct | Items |
|---|---|
| Perceived Profile Disclosure | **Pro_Dis_1 -** I have a comprehensive profile on LinkedIn.<br>**Pro_Dis_2 -** I have a detailed profile on LinkedIn.<br>**Pro_Dis_3 -** My profile tells a lot about me.<br>**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<br>**A_Partici_2-** Share something on your wall<br>**A_Partici_3-** Like what connections post. |
| Passive Consumption | **P_Consum_1-** Follow the news of your connections.<br>**P_Consum_2-** Look through the News-feed.<br>**P_Consum_3-** Click on the content shared by connections. |
| Network Size/degree | How many 1st level connections do you currently have on LinkedIn? |

Table 4.2 (continued) Measurement Items for Constructs

| Construct | Items |
|---|---|
| Perceived Social Connectedness | **Soc_Con_1-** Feel close to the people in my connection list.<br>**Soc_Con_2-** Have a feeling of being connected to others.<br>**Soc_Con_3-** am updated about my connections.<br>**Soc_Con_4-** Stay in touch with my connections.<br>**Soc_Con_5-** Keep contact with the people in my connection list.<br>**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<br>**V_Netw_2-** I get information about job market from my LinkedIn connections/groups<br>**V_Netw_3-** Through my network connections on LinkedIn I can get easily valuable referrals.<br>**V_Netw_4-** My LinkedIn connections elevate my social credentials in my field of work.<br>**V_Netw_5-** Some of my LinkedIn connections/groups boost my identity and recognition.<br>**V_Netw_6-** Information shared by my LinkedIn connections/groups is sufficiently timely. |

## 4.5 Pilot Test and Research Ethics

In order to assess the validity and reliability of the measurement instrument, a pilot study was conducted prior to the main data collection. The pilot study consisted of 20 participants. Participants were recruited from the student population at McMaster and Ryerson Universities. Results from the pilot study were used to identify and resolve potential problems with the study’s survey questions. However, no problems with the questions were identified from the pilot study. Table 4.3 shows the results of the reliability analysis for constructs in the research model. Ethics approval for both pilot and main studies was secured prior to data collection in the pilot study, from both McMaster and Ryerson Research Ethics Boards.

Table 4.3 Pilot-test Constructs' Reliability Results

| Construct | Cronbach's alpha |
|---|---|
| Perceived Profile Disclosure | 0.822 |
| Active Participation | 0.711 |
| Passive Consumption | 0.944 |
| Perceived Social Connectedness | 0.950 |
| Perceived Networking Value | 0.795 |

### 4.6 Data Analysis

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) (Gefen et al., 2000). PLS (a component-based SEM technique) is preferred over AMOS or LISREL (a covariance-based SEM technique) because it imposes minimum demands in terms of sample size, sample data distribution, and residuals distribution (Chin, 1998). According to Hair et al. (2016), the systematic evaluation of PLS-SEM results, as shown in Table 4.4, includes two stages: (1) evaluation of the measurement model, and (2) evaluation of the structural model (Hair et al., 2016).

Table 4.4 Systematic Evaluation of PLS-SEM Results (Hair et al., 2016)

| **Evaluation of the measurement model** |
|---|
| • Internal consistency (Cronbach's alpha, composite reliability)<br>• Convergent validity (indicator reliability, average variance extracted)<br>• Discriminant validity (cross loadings, Fornell-Larcker criterion, HTMT) |
| **Evaluation of the Structural Model** |
| • Assess the structural model for collinearity issues<br>• Coefficient of determination ($R^2$)<br>• Size and significance of path coefficients<br>• $f^2$ effect sizes<br>• Predictive relevance ($Q^2$)<br>• $q^2$ effect sizes |

### 4.6.1 Evaluation of the Measurement Model

As outlined in Table 4.4, validation of the measurement model includes internal consistency (Cronbach's alpha, composite reliability), convergent validity (Indicator's outer loading, indicator reliability, average variance extracted), and discriminant validity (cross loadings, Fornell-Larcker criterion, HTMT) (Hair et al., 2016).

Internal consistency is defined as the extent to which a variable or set of variables is consistent in what it intends to measure (Chin, 2010; Straub, Boudreau, & Gefen, 2004) Cronbach's alpha as a traditional measure for internal consistency is based on the intercorrelations of the observed indicator variables, whereas composite reliability considers the outer loadings and measurement errors of indicator variables. Cronbach's alpha and composite reliability values of 0.60 to 0.70 are acceptable in exploratory research. However, most researchers regard values between 0.70 and 0.90 as ideal (Chin, 1998; Hair et al., 2016; Nunnally, J. C., & Bernstein, 1994).

Convergent validity is defined as "the extent to which a measure correlates positively with alternative measures of the same construct" (Hair et al., 2016, p.112). Convergent validity will be examined through indicator outer loading, indicator reliability (also known as communality) and the average variance extracted (AVE) by each construct. An indicator outer loading on a construct indicates how much in common that indicator has with that construct. Indictor reliability, also known as communality, is the square of a standardized indicator's outer loading, which represents how much of the variation in an item is explained by the construct and is described as the variance extracted from the item (Hair et al., 2016). At a minimum, the outer loadings of all indicators should be statistically significant. In addition, AVE defined as the grand mean value of the squared loadings of the indicators associated with the construct, should exceed the variance due to measurement error for that construct (i.e., AVE should be above 0.5) (Boudreau, Gefen, & Straub, 2001; Fornell & Larcker, 1981; Gefen & Straub, 2005).

Discriminant validity is defined as "the extent to which a construct is truly distinct from other constructs by empirical standards" (Hair et al., 2016, p.115). Discriminant validity can be assessed by examining the cross loadings of the indicators. Specifically, an indicator's outer loading on the associated construct should be greater than all of its loadings on other constructs (Hair, Ringle, & Sarstedt, 2011). The second and more conservative approach to assess discriminant validity is the Fornell-Larcker criterion which requires the square root of each construct's AVE to be greater than its highest correlation with any other construct (Fornell & Larcker, 1981). The more recent approach to assess discriminant validity is the heterotrait-monotrait ratio (HTMT) which is the ratio of the between-trait correlations to the within-trait correlations. In other words, HTMT is simply “the mean of all correlations of indicators across constructs measuring different constructs relative to the mean of the average correlations of indicators measuring the same construct” (Hair et al., 2016, p.118; Henseler, Ringle, & Sarstedt, 2015). According to Henseler et al. (2015), any HTMT value above 0.85 suggests a lack of discriminant validity. Table 4.5 summarizes all criteria used in this study to assess the validity of the research measurement model.

Table 4.5 Criteria for Assessing Validity of the Measurement Model

| **Criteria** | **Reference(s)** |
|---|---|
| **Internal Consistency** | |
| Cronbach’s alpha > 0.70 | Hair et al (2016), Cronbach (1951), Nunnally and Bernstein, (1994) |
| Composite Reliability (CR) > 0.70 | Nunnally and Bernstein (1994), Chin (1998) |
| **Convergent Validity** | |
| Item Outer loading> 0.7 | Hair et al. (2016) |
| Indicator reliability > 0.5 | Hair et al. (2016) |
| Average Variance Extracted (AVE) > 0.50 | Chin (1998), Fornell and Larcker (1981) |

Table 4.5 (continued) Criteria for Assessing Validity of the Measurement Model

| **Criteria** | **Reference(s)** |
|---|---|
| **Discriminant Validity** | |
| Cross Loadings: An indicator's outer loading on the associated construct should be greater than all of its loadings on other constructs | Chin (1998), Hair et al. (2016) |
| Fornell-Larcker: The square root of each construct's AVE to be greater than its highest correlation with any other construct | Chin (1998), Hair et al. (2016) |
| heterotrait-monotrait ratio (HTMT) < 0.85 | Henseler et al. (2015) |

### 4.6.2 Evaluation of the Structural Model

Evaluating PLS-SEM structural model involves assessing the structural model for collinearity issues, coefficients of determination ($R^2$ values), the size and the significance of the path coefficients, $f^2$ effect sizes, predictive relevance ($Q^2$), and $q^2$ effect sizes (Chin, 2010; Falk & Miller, 1992; Hair et al., 2016). Figure 4.1 shows the steps used for evaluating the PLS-SEM structural model for this study based on the guideline proposed by Hair et al. (2016).

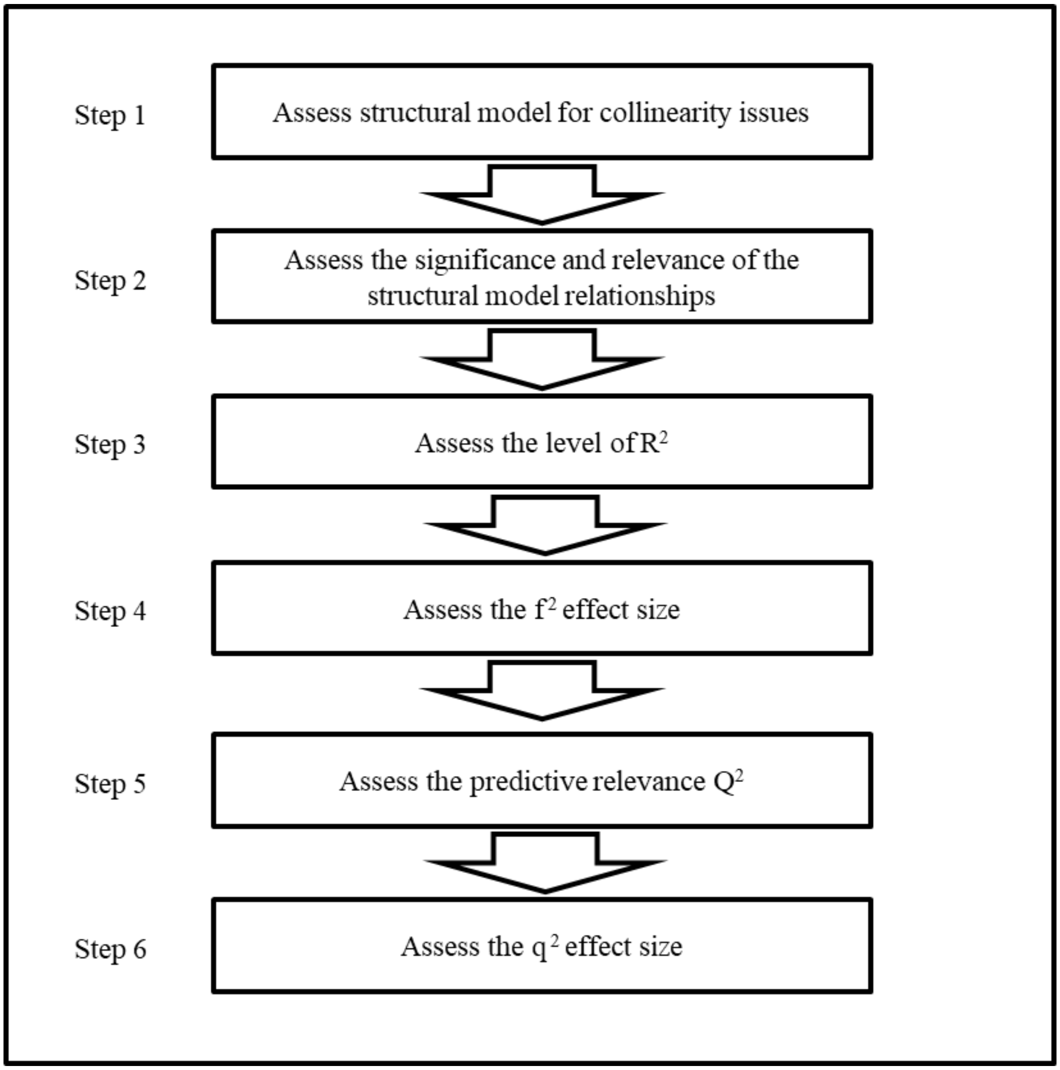



Figure 4.1 Structural Model Assessment (Hair et al., 2016)

The first step in evaluating the PLS-SEM structural model is to assess collinearity issues. Each set of predictor constructs should be examined separately for each endogenous construct in the structural model. VIF value below 5.00 indicates the lack of collinearity issues. For VIF above 5, researchers should consider eliminating constructs, merging predictors into a single construct, or creating higher-order constructs (Hair et al., 2016).

Assessing the significance and relevance of the structural model relationships is the next step in evaluating the PLS-SEM structural model. The significance of relationships can be tested by examining the empirical t value, the p value, or bootstrapping confidence interval. The relevance of relationships can be assessed by the size of relationships. The path coefficients have standardized values between -1 and + 1. Strong positive and negative relationships have estimated path coefficients close to + 1 and -1 respectively and they are almost always statistically significant (i.e., different from zero in the population). However, the path coefficients in the structural model may be significant, but their sizes may be so small which, from a managerial perspective, means that they are not worthwhile to be considered. Therefore, an analysis of the relative importance of relationships is crucial for interpreting the SEM-PLS results and drawing appropriate managerial conclusions (Chin, 2010).

The third step to assess the PLS-SEM structural model is to examine the level of $R^2$, the coefficient of determination, which represents "the amount of variance in the endogenous constructs explained by all of the exogenous constructs linked to it" (Hair et al., 2016, p.198). The $R^2$ value ranges from 0 to 1 with higher levels indicating higher levels of predictive accuracy. According to Hair, Jr. et al. (2016), $R^2$ values of 0.75, 0.50, or 0.25 for endogenous latent variables can be respectively described as substantial, moderate, or weak (Hair et al., 2016, 2011; Henseler, Ringle, & Sinkovics, 2009).

The next step in the assessment of PLS-SEM structural model is to evaluate the $f^2$ value which is defined as the change in the $R^2$ value when a specified exogenous construct is omitted from the model. In other words, $f^2$ values show the impact of each exogenous construct on the endogenous constructs (Cohen, 2013; Hair et al., 2016). The effect size, $f^2$, can be calculated as:

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

$f^2$ values of 0.02, 0.15, and 0.35 represent small, medium, and large effects of the exogenous latent variable respectively (Hair et al., 2016).

The fifth step in the assessment of PLS-SEM structural model is to assess Stone-Geisser's $Q^2$ value of the model which represents the model's predictive relevance (Geisser, 1974; Hair et al., 2016; M. Stone, 1974). While $R^2$ as a measure of predictive accuracy indicates how much exogenous constructs are relevant, $Q^2$ value of the model indicates how much an endogenous construct is relevant in the model. The blindfolding procedure for a specified omission distance D is used for measuring the $Q^2$ value. The $Q^2$ value can be calculated as:

$$\boldsymbol{Q^2 = 1 - \frac{\sum_D SSE_D}{\sum_D SSO_D}}$$

Where D = mission distance
SSO = sum of squares of observations
SSE = sum of squares of prediction errors

$Q^2$ values larger than 0 suggest that the model has predictive relevance for a certain endogenous construct. In contrast, values of 0 and below indicate a lack of predictive relevance (Hair et al., 2016).

Finally, effect size $q^2$ represents the relative importance of each predictor (exogenous construct) on predictive relevance of an endogenous construct. Similar to $f^2$ effect size, the $q^2$ effect size can be calculated by the following formula:

$$f^2 = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}}$$

$q^2$ values of 0.02, 0.15, and 0.35 indicate that an exogenous construct has a small, medium, or large predictive relevance for a certain endogenous construct respectively (Hair et al., 2016).

## 4.7 Common Method Variance

Common Method Variance (CMV) refers to the variance that is attributable to the measurement method rather than the constructs or the relationships among constructs in the research model (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003, p.1; Straub et al., 2004). Method variance is one of the main sources of systematic measurement error which could be a threat to the validity of research results and may arise from variety of sources such as length of survey, scale type, response format, measurement context effect (e.g. predictors and outcome variable measured at the same point in time (Podsakoff et al., 2003).

Podsakoff et al. (2003) suggest a number of ways to reduce the threat of CMV such as ensuring participants' anonymity, avoiding vague and unfamiliar concepts in questions, and minimizing the required time for responding to the whole survey. In this study, these suggestions are taken into account to reduce the potential threat of CMV. For example, the data collection procedure was designed in a way that respondents' anonymity was protected. In addition, the survey was designed in a way that it took 20-30 minutes to complete. Moreover, quality questions were placed in the middle and close to the end of the survey to make sure that participants continued to pay attention to the survey questions.

To assess the potential impact of CMV in this research, a procedure proposed by Kock (2015) was selected. Through this procedure, variance inflation factors (VIFs) are calculated for all latent variables in a model. The occurrence of a VIF greater than 3.3 is proposed as an indication that common method bias was present in a model (Kock, 2015).

# Chapter 5 : Data Analysis and Results

This chapter covers the following sections: data collection and screening, sample demographics, descriptive statistics, exploratory statistics, evaluation of measurement and structural models, common method variance assessment, post-hoc analysis, and the results of the analysis of the single open-ended question asked in the survey.

## 5.1 Data Collection and Screening

This study targeted young and mid-aged adults who actively use LinkedIn. Participants were recruited from the target population at Ryerson and McMaster Universities as well as through Qualtrics, a research service firm. As discussed earlier, the minimum sample size requirement for this study is 112. However, in total, 420 responses were collected for this study, of which 385 were usable. Thirty-five responses were omitted due to trivial responses (e.g., selecting the same value for every question), incompleteness, wrong answers to the quality questions, or duplicate responses (as identified by IP address).

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 (Meyers, Gamst, & Guarino, 2016). Applying a chi-square test ($p<.001$, df=4) to four composite variables (Perceived Profile Disclosure, Active Participation, Passive Consumption, and Perceived 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 reduced to 377.

## 5.2 Demographics of Respondents

Table 5.1 to 5.4 provide the result for participants' age, gender, the level of education, and employment status. In total, 69.5% of participants were between 18 and 34 years old. 62.6 % of participants were female. With respect to education level, 78.8% of participants held an undergrad or college degree, while 20.9% had a master's degree or higher. Regarding employment status, 47.7 % of participants were students, while 45.6 % were employed (full time or part time).

Table 5.1 Participants' Age

| Age Category | Frequency | Percent | Cumulative Percent |
|---|---|---|---|
| **18-24** | 159 | 42.2 | 42.2 |
| **25-34** | 103 | 27.3 | 69.5 |
| **35-44** | 108 | 28.6 | 98.1 |
| **45-54** | 6 | 1.6 | 99.7 |
| **Prefer Not To Say/Not Applicable** | 1 | 0.3 | 100.0 |
| **Total** | 377 | 100.0 | |

Table 5.2 Participants' Gender

| Gender | Frequency | Percent | Cumulative Percent |
|---|---|---|---|
| **Female** | 236 | 62.6 | 62.6 |
| **Male** | 137 | 36.3 | 98.9 |
| **Other** | 3 | 0.8 | 99.7 |
| **Prefer Not To Say/Not Applicable** | 1 | 0.3 | 100.0 |
| **Total** | 377 | 100.0 | |

Table 5.3 Participants' Education

| Education | Frequency | Percent | Cumulative Percent |
|---|---|---|---|
| **High School Diploma** | 167 | 44.3 | 44.3 |
| **College Diploma** | 33 | 8.8 | 53.1 |
| **University-Undergraduate Bachelor's Degree** | 97 | 25.7 | 78.8 |
| **University-Master's Degree** | 62 | 16.4 | 95.2 |
| **University-Doctoral Degree** | 17 | 4.5 | 99.7 |
| **Prefer Not To Say/Not Applicable** | 1 | 0.3 | 100.0 |
| **Total** | 377 | 100.0 | |

Table 5.4 Participants' Employment Status

| Employment Status | Frequency | Percent | Cumulative Percent |
|---|---|---|---|
| **Employed (Full time or part time)** | 172 | 45.6 | 45.6 |
| **Out of Work** | 13 | 3.4 | 49.1 |
| **Homemaker** | 7 | 1.9 | 50.9 |
| **Student** | 180 | 47.7 | 98.7 |
| **Retired** | 1 | 0.3 | 98.9 |
| **Prefer Not To Say/Not Applicable** | 4 | 1.1 | 100.0 |
| **Total** | 377 | 100.0 | |

### 5.3 Descriptive Statistics

The descriptive statistics of the measurement items used in this study is provided in Table 5.5. Although the PLS analysis method does not require normal distribution for data, non-normality of data regarding skewness and kurtosis is not a severe issue. The skewness values of the indicators are within the -1 and +1 acceptable range. The only exceptions are the A_Partici_1 and A_Partici_2 indicators (for the Active Participation variable), which have a skewness slightly above 1 and thus exhibit a slight degree of non-normality. However, because there are only three indicators measuring this reflective construct (Active Participation), and the degree of skewness of these indicators are not severe, these deviations from normality are not considered an issue, and the indicators are retained.

Tables 5.6 to 5.8 shows participants' network size, LinkedIn membership duration, and average weekly engagement in hours. 80.6% of participants in this research had a network size of less than 300. Concerning the LinkedIn membership duration, 36.6% of participants in this research had joined LinkedIn for less than 2 years. 76.9% of participants in this research spent less than 4 hours per week on LinkedIn. This pattern of usage is in alignment with global LinkedIn users. According to Statista.com (2017), 75% of global LinkedIn users spend less than 4 hours per week on this site.

Table 5.5 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 |

Pro_Dis = Perceived Profile Disclosure; Netw_S = Network Size; Soc_Con = Perceived Social Connectedness; A_Partici = Active Participation; P_Consum = Passive Consumption; V_Netw = Perceived Networking Value

Table 5.6 Participants' Network Size

| Network Size | Frequency | Percent | Cumulative Percent |
|---|---|---|---|
| **0-50** | 118 | 31.3 | 31.3 |
| **51-100** | 70 | 18.6 | 49.9 |
| **101-150** | 40 | 10.6 | 60.5 |
| **151-200** | 36 | 9.5 | 70.0 |
| **201-250** | 21 | 5.6 | 75.6 |
| **251-300** | 19 | 5.0 | 80.6 |
| **301-400** | 17 | 4.5 | 85.1 |
| **401-500** | 19 | 5.0 | 90.2 |
| **500+** | 37 | 9.8 | 100.0 |
| **Total** | 377 | 100.0 | |

Table 5.7 Participants' LinkedIn Membership Duration

| LinkedIn Membership Duration | Frequency | Percent | Cumulative Percent |
|---|---|---|---|
| **Less than 6 months** | 27 | 7.2 | 7.2 |
| **Months to Year** | 33 | 8.8 | 15.9 |
| **1-2 Years** | 78 | 20.7 | 36.6 |
| **More Than 2 Years** | 239 | 63.4 | 100.0 |
| **Total** | 377 | 100.0 | |

Table 5.8 Participants' LinkedIn engagement (hours per week)

| LinkedIn Engagement (hours) | Frequency | Percent | Cumulative Percent |
|---|---|---|---|
| **0-2** | 194 | 51.5 | 51.5 |
| **3-4** | 96 | 25.5 | 76.9 |
| **5-6** | 39 | 10.3 | 87.3 |
| **7-8** | 22 | 5.8 | 93.1 |
| **8+** | 26 | 6.9 | 100.0 |
| **Total** | 377 | 100.0 | |

## 5.4 Evaluation of the Measurement Model

As outlined in section 4.6.1, assessment of a reflective 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. In this section, each of these criterion for the assessment of reflective measurement model is addressed. It is important to note that Network Size (single item construct) is not included as it is not relevant for this analysis.

Internal consistency was assessed via Cronbach's alpha and composite reliability (Table 5.9). All constructs passed the threshold value of 0.6 for Cronbach's alpha composite reliability (Hair et al., 2016). Hence, it can be concluded that constructs in the measurement model have satisfactory internal consistency.

Table 5.9 Internal Consistency Reliability Results

| | **Cronbach's Alpha** | **Composite Reliability** |
|---|---|---|
| | > 0.6 | > 0.6 |
| **A_Partici** | 0.885 | 0.929 |
| **P_Consum** | 0.934 | 0.957 |
| **Pro_Disc** | 0.929 | 0.950 |
| **Soc_Con** | 0.935 | 0.949 |
| **Val_Netw** | 0.860 | 0.894 |

A_Partici = Active Participation;; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

Convergent validity was assessed via items' outer loadings, indicators' reliability, and average variance extracted (AVE) (Table 5.10).

Table 5.10 Convergent Validity Results

| | **Outer Loadings** | **Indicator Reliability** | **AVE** |
|---|---|---|---|
| | > **0.7** | > **0.5** | > **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 | |

A_Partici = Active Participation; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; V_Netw = Perceived Networking Value

As can be seen in Table 5.10, 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 (Hair et al., 2016). Hence, it can be concluded that constructs in the measurement model have satisfactory convergent validity. Regarding V_Netw_1 ('I receive information about job opportunities from my LinkedIn connections/groups'), in line with the guideline (Figure 5.1) proposed by Hair et al. (2016), 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).

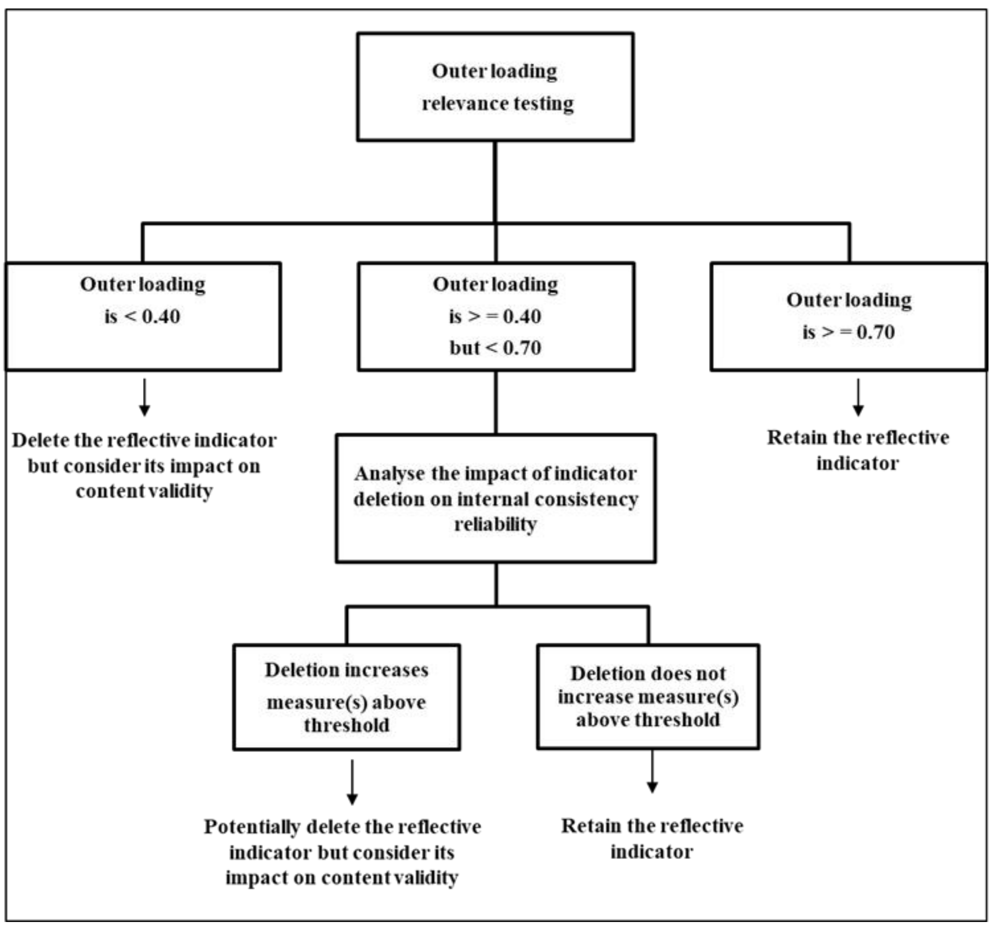



Figure 5.1 Guideline for Outer Loading Relevance Testing (Hair et al., 2016, p.114)

Finally, the measurement model was tested in terms of discriminant validity. Tables 5.11 to 5.13 shows the results of items' cross loadings, Fornell-Larcker Criterion, and the heterotrait-monotrait ratio (HTMT). As can be seen, each indicator's outer loading on its associated construct is greater than its loadings on other constructs (Table 5.11). In addition, the square root of each construct's AVE is greater than its highest correlation with any other construct (Table 5.12), and finally, all HTMT values in Table 5.13 are lower than the threshold value of 0.85 (as per Henseler et al., 2015).

Table 5.11 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** |

A_Partici = Active Participation; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; V_Netw = Perceived Networking Value

Table 5.12 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** |

A_Partici = Active Participation; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

- Bold values in the table are the square root of each construct's AVE

Table 5.13 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 | |

A_Partici = Active Participation; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

Table 5.14 shows a summary of measurement model assessment results including internal consistency, convergent validity, and discriminant validity (HTMT). It is important to note that as PLS-SEM does not consider any distributional assumptions, standard parametric significance tests cannot be applied to determine whether HTMT is significantly different from 1. As such, bootstrapping procedure can be used to derive a bootstrap confidence interval for the HTMT statistic (Henseler et al., 2015). A confidence interval containing the value of 1 indicates a lack of discriminant validity for HTMT statistic (Hair et al., 2016).

Table 5.14 Measurement Model Assessment Results

| Latent Variable | Indicators | Convergent Validity | | | Internal Consistency Reliability | | Discriminant Validity HTMT |
|---|---|---|---|---|---|---|---|
| | | Loadings | Indicator Reliability | AVE | Composite Reliability | Cronbach's Alpha | Values less than 0.85 and confidence interval does not include 1 |
| | | > 0.70 | > 0.50 | > 0.50 | > 0.70 | > 0.70 | |
| **Active Participation** | A_Partici_1 | 0.936 | 0.876 | 0.814 | 0.929 | 0.885 | Yes |
| | A_Partici_2 | 0.908 | 0.824 | | | | |
| | A_Partici_3 | 0.861 | 0.741 | | | | |
| **Passive Consumption** | P_Consum_1 | 0.933 | 0.870 | 0.882 | 0.957 | 0.934 | Yes |
| | P_Consum_2 | 0.941 | 0.885 | | | | |
| | P_Consum_3 | 0.944 | 0.891 | | | | |
| **Perceived Profile Disclosure** | Pro_Dis_1 | 0.916 | 0.839 | 0.825 | 0.950 | 0.929 | Yes |
| | Pro_Dis_2 | 0.926 | 0.857 | | | | |
| | Pro_Dis_3 | 0.914 | 0.835 | | | | |
| | Pro_Dis_4 | 0.875 | 0.766 | | | | |
| **Perceived Social Connectedness** | Soc_Con_1 | 0.831 | 0.691 | 0.757 | 0.949 | 0.935 | Yes |
| | 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 | | | | |
| **Perceived Networking Value** | V_Netw_1 | 0.689 | 0.475 | 0.586 | 0.894 | 0.86 | Yes |
| | 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 | | | | |

## 5.5 Evaluation of Structural Model

As described in the section 4.6.2, evaluating a PLS-SEM structural model involves assessing the structural model for collinearity issues, coefficients of determination ($R^2$ values), the size and the significance of the path coefficients, $f^2$ effect sizes, predictive relevance (Q2), and q2 effect sizes. In this section, the results of PLS-SEM structural model analysis are presented.

### 5.5.1 Assessment the Structural Model for Collinearity

Table 5.15 shows the VIF values of all sets of predictor constructs in the structural model. Specifically, the following sets of predictor constructs for collinearity 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 profile disclosure as predictors of perceived networking value. As can be seen in Table 5.15, all VIF values are clearly below the threshold of 5 (Hair et al., 2016). Therefore, it can be concluded that collinearity among the predictor constructs is not a critical issue in the structural model.

Table 5.15 Collinearity Assessment of 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** | | | | | | |

A_Partici = Active Participation; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

5.5.2 Assessment of the Path Coefficients in the Structural Model

To determine the path coefficients and whether the relationships in the structural model are significant, the bootstrapping procedure was used. Figure 5.2 shows the coefficient and significance level of all relationships in the structural model (using a bootstrapping procedure with 5000 samples). Assuming a 5% significance level, as can be seen in Figure 5.2 all paths except for Active Participation → Network Size and Network Size → Perceived Networking Value are significant.

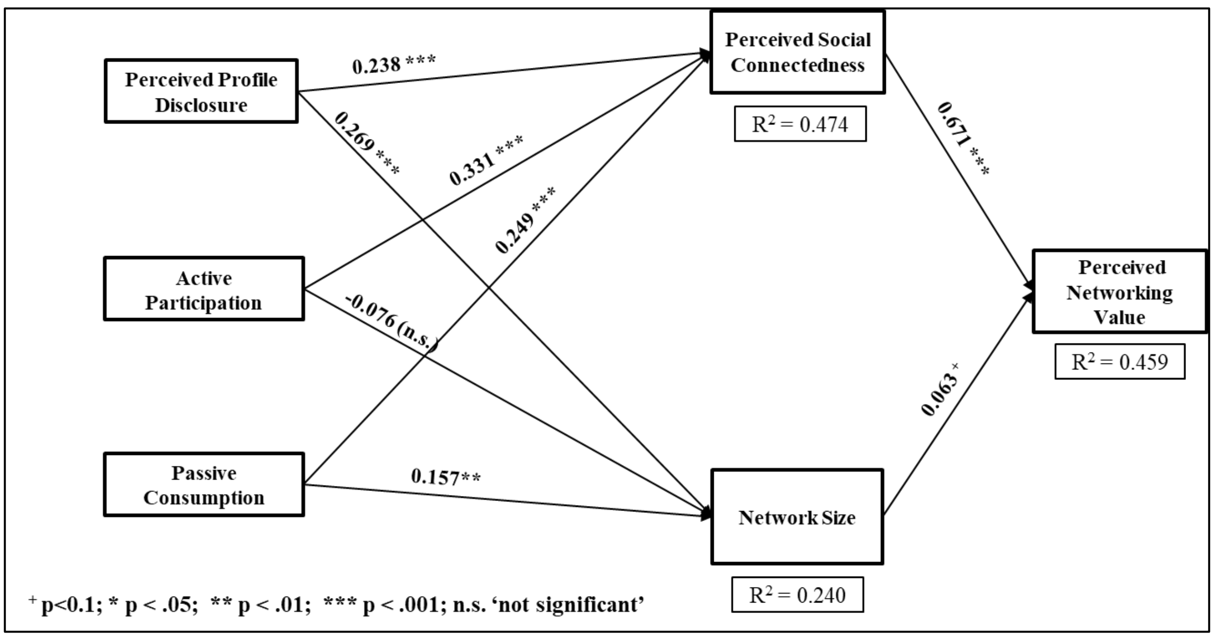



Figure 5.2 Path Coefficients and Significance Levels in the Structural Model

As can be seen in Figure 5.2, active participation has the strongest effect on perceived social connectedness (0.331, $p<0.001$), followed by passive consumption (0.249, $p<0.001$) and perceived profile disclosure (0.238, $p<0.001$). In contrast, perceived profile disclosure has the strongest effect on network size (0.269, $p<0.001$), followed by passive consumption (0.157, $p<0.01$). Active participation turns out to have no significant effect on network size. Perceived social connectedness appeared to have a strong positive effect on perceived networking value (0.671, $p<0.001$). In contrast, network size has very little effect on perceived network size (significant at 0.1 level) which suggests that larger network size by itself may not be associated with the increased perception of networking value.

Table 5.16 shows the results of hypotheses testing. As can be seen, all hypotheses except for H2-b (Active Participation → Network Size) are supported assuming $p<0.1$ significance level. Table 5.17 shows specific indirect effect sizes. In addition, through examining total effects (direct and indirect effects), it can be evaluated how strongly each of predictor constructs (perceived profile disclosure, active participation, passive consumption) ultimately influence the key target variable, perceived networking value. As can be seen in Table 5.18, active participation has the strongest total effect on perceived networking value (0.217, $p<0.001$), followed by perceived profile disclosure (0.178, $p<0.001$) and passive consumption (0.178, $p<0.001$).

Table 5.16 Hypotheses Test Results

| Hypothesis | Path | Path coefficient | Sig. level (p-value) | Validation |
|---|---|---|---|---|
| H1-a | Profile Disclosure → Social Connectedness | 0.238 | 0.000 | Supported |
| H1-b | Profile Disclosure → Network Size | 0.269 | 0.000 | supported |
| H2-a | Active Participation → Social Connectedness | 0.331 | 0.000 | Supported |
| H2-b | Active Participation → Network Size | -0.076 | 0.269 | Not Supported |
| H3-a | Passive Consumption → Social Connectedness | 0.249 | 0.000 | Supported |
| H3-b | Passive Consumption → Network Size | 0.157 | 0.008 | Supported |
| H4 | Social Connectedness → Networking Value | 0.671 | 0.000 | Supported |
| H5 | Network Size → Networking Value | 0.063 | 0.094 | Marginally Supported |

Table 5.17 Specific Indirect Effect Size Results

| | Sample Mean (M) | P Values |
|---|---|---|
| **A_Partici -> Netw_S -> Val_Netw** | -0.005 | 0.396 |
| **P_Consum -> Netw_S -> Val_Netw** | 0.010 | 0.218 |
| **Pro_Disc -> Netw_S -> Val_Netw** | 0.017 | 0.121 |
| **A_Partici -> Soc_Con -> Val_Netw** | 0.222 | 0.000 |
| **P_Consum -> Soc_Con -> Val_Netw** | 0.167 | 0.000 |
| **Pro_Disc -> Soc_Con -> Val_Netw** | 0.160 | 0.000 |

A_Partici = Active Participation; Netw_S = Network Size; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

Table 5.18 Total Effect Size Results (direct and indirect effects)

| | Sample Mean (M) | P Values |
|---|---|---|
| **A_Partici -> Netw_S** | -0.076 | 0.269 |
| **A_Partici -> Soc_Con** | 0.331 | 0.000 |
| **A_Partici -> Val_Netw** | 0.217 | 0.000 |
| **Netw_S -> Val_Netw** | 0.063 | 0.094 |
| **P_Consum -> Netw_S** | 0.157 | 0.008 |
| **P_Consum -> Soc_Con** | 0.249 | 0.000 |
| **P_Consum -> Val_Netw** | 0.178 | 0.000 |
| **Pro_Disc -> Netw_S** | 0.269 | 0.000 |
| **Pro_Disc -> Soc_Con** | 0.238 | 0.000 |
| **Pro_Disc -> Val_Netw** | 0.178 | 0.000 |
| **Soc_Con -> Val_Netw** | 0.671 | 0.000 |

A_Partici = Active Participation; Netw_S = Network Size; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

### 5.5.3 Evaluation of the Coefficients of Determination ($R^2$ values)

Table 5.19 shows the results of $R^2$ values of endogenous variables. As discussed in section 4.6.2, the $R^2$ coefficient as a measure of model's predictive power represents the amount of variance in the endogenous variable explained by all of the exogenous constructs linked to it. Following the Hair et al. (2016) 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.

Table 5.19 $R^2$ Adjusted Values Results

| | Sample Mean (M) | P Values |
|---|---|---|
| Netw_S | 0.240 | 0.000 |
| Soc_Con | 0.474 | 0.000 |
| Val_Netw | 0.459 | 0.000 |

Netw_S = Network Size; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

### 5.5.4 Assessment of the $f^2$ Effect Sizes

Table 5.20 shows the effect sizes $f^2$ for all structural model relationships. As discussed in section 4.6.2, the $f^2$ value shows how much the $R^2$ changes when a specified exogenous construct is omitted from the model. As can be seen in Table 5.20, passive consumption and active participation have no significant effect (in terms of $f^2$) on network size, whereas perceived profile disclosure has a significant effect size of 0.074 on network size, however, based on Hair et al. (2016) guideline, its effect size can be considered weak. In contrast, active participation and perceived profile disclosure have moderate to weak effects on social connectedness (0.105 and 0.084 respectively), whereas passive consumption has a weak effect size of 0.068 on social connectedness. When it comes to predicting networking value, social connectedness has a strong effect size of 0.793, whereas network size has no significant effect.

Table 5.20 $f^2$ Effect Size Results

| | **Sample Mean (M)** | **P Values** |
|---|---|---|
| **A_Partici -> Netw_S** | 0.007 | 0.637 |
| **A_Partici -> Soc_Con** | 0.105 | 0.001 |
| **Netw_S -> Val_Netw** | 0.006 | 0.439 |
| **P_Consum -> Netw_S** | 0.021 | 0.269 |
| **P_Consum -> Soc_Con** | 0.068 | 0.034 |
| **Pro_Disc -> Netw_S** | 0.074 | 0.009 |
| **Pro_Disc -> Soc_Con** | 0.084 | 0.022 |
| **Soc_Con -> Val_Netw** | 0.793 | 0.000 |

A_Partici = Active Participation; Netw_S = Network Size; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

### 5.5.5 Assessment of the Predictive Relevance $Q^2$

To assess the predictive relevance of the path model, the Blindfolding procedure in the PLS-SEM was used. $Q^2$ values represent the predictive relevance of endogenous variables in the model. Table 5.21 shows the results of $Q^2$ values for all three endogenous variables (Netw_S, Soc_Con, and Val_Netw). SSO and SSE columns in the table show the sum of the squared observations and the sum of the squared prediction errors respectively. As shown, the $Q^2$ values of all endogenous variables are above zero. More precisely, social connectedness has the highest $Q^2$ value (0.335), followed by networking value (0.235) and network size (0.219). These results provide clear support for the predictive relevance of each of these endogenous variables in the model.

Table 5.21 $Q^2$ Results

| | **SSO** | **SSE** | **$Q^2$ (=1-SSE/SSO)** |
|---|---|---|---|
| **A_Partici** | 1,131.00 | 1,131.00 | |
| **Netw_S** | 377.00 | 294.256 | 0.219 |
| **P_Consum** | 1,131.00 | 1,131.00 | |
| **Pro_Disc** | 1,508.00 | 1,508.00 | |
| **Soc_Con** | 2,262.00 | 1,503.765 | 0.335 |
| **Val_Netw** | 2,262.00 | 1,730.678 | 0.235 |

A_Partici = Active Participation; Netw_S = Network Size; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

### 5.5.6 Assessment of the $q^2$ Effect Sizes

The final step in the evaluation of the PLS-SEM structural model is to assess the $q^2$ effect sizes. As discussed in section 4.6.2, the $q^2$ effect size value shows the relative impact of each construct in the model on predictive relevance of a certain endogenous variable. Table 5.22 shows the results of $q^2$ effect sizes for all relationships in the structural model. As shown, social connectedness has a moderate predictive relevance for networking value, whereas network size has no predictive relevance for networking value. Perceived profile disclosure, active participation, and passive consumption have weak predictive relevance for their associated endogenous variables (social connectedness and network size).

Table 5.22 $q^2$ Results

| | **Soc_Con** | **Netw_S** | **Val_Netw** |
|---|---|---|---|
| **Pro_Disc** | 0.044 | 0.063 | |
| **A_Partici** | 0.053 | 0.000 | |
| **P_Consum** | 0.035 | 0.012 | |
| **Soc_Con** | | | 0.288 |
| **Netw_S** | | | 0.003 |

A_Partici = Active Participation; Netw_S = Network Size; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

## 5.6 Common Method Variance

As discussed in section 4.7, to assess the potential impact of CMV in this research, a procedure proposed by Kock (2015) was selected. Through this procedure, variance inflation factors (VIFs) are calculated for all latent variables in a model. The occurrence of a VIF greater than 3.3 is proposed as an indication that common method bias was present in a model (Kock, 2015). Table 5.23 shows the results of running the procedure proposed by Kock (2015). As shown, all VIF values are less than 3.3 which clearly shows the lack of common method variance in the model.

Table 5.23 Results of Common Method Variance Assessment

| | A_Partici | Netw_S | P_Consum | Pro_Disc | Soc_Con | Val_Netw |
|---|---|---|---|---|---|---|
| A_Partici | | 2.373 | 1.692 | 2.108 | 1.985 | 2.127 |
| Netw_S | 1.176 | | 1.154 | 1.050 | 1.178 | 1.178 |
| P_Consum | 1.623 | 2.260 | | 2.066 | 2.005 | 1.956 |
| Pro_Disc | 1.535 | 1.408 | 1.556 | | 1.502 | 1.493 |
| Soc_Con | 1.941 | 1.978 | 2.015 | 1.962 | | 1.778 |
| Val_Netw | 2.056 | 2.064 | 1.950 | 1.950 | 1.794 | |

A_Partici = Active Participation; Netw_S = Network Size; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

## 5.7 Post-hoc Analysis

The first post-hoc analysis focuses on the assessment of possible differences between sub-samples (Ryerson/McMaster sample versus Qualtrics sample). Next, the role of control variables on the proposed model will be evaluated.

### 5.7.1 Assessment of Sub-Samples Differences

Data from two different sources in this study was collected: (1) populations at Ryerson University and McMaster University (221 cases from Ryerson and 9 cases from McMaster) and (2) the general population in Ontario through Qualtrics, a market research firm (147 cases). This may cause heterogeneity in data. Heterogeneity in data means that the used data stems from different populations. According to Hair et al. (2016), it mainly results from differences in observable characteristics of data such as gender, age, education, etc. Failure to consider heterogeneity in data can undermine the validity of PLS-SEM results, and it can lead to drawing incorrect conclusions (Becker, Rai, Ringle, & Völckner, 2013; Hair, Sarstedt, Ringle, & Mena, 2012).

Table 5.24 compares the main characteristics of these two sub-samples. Individuals in sub-sample 1 (Ryerson/McMaster University, 230 cases) were mainly younger adults aged less than 34 years old with high school or college diploma. In contrast, individuals in sub-sample 2 (Qualtrics, 147 cases) were, on average, older with higher education (undergrad and higher) and joined LinkedIn for more than two years.

Table 5.24 Characteristics of Two Sub-Samples in the Research Dataset

| Sub-sample 1<br>Ryerson/McMaster University (230 cases) | Sub-sample 2<br>Qualtrics (147 cases) |
|---|---|
| • 63.5% have a high school and college diploma.<br>• 40.9% joined LinkedIn for less than two years.<br>• 76.1% aged 18-34 years old.<br>• 64.3% are female.<br>• 54.3% not seeking for a job. | • 63.3% have undergrad and higher education.<br>• 70.1% joined LinkedIn for more than two years.<br>• 39.5% aged 35-44.<br>• 59.8% are female.<br>• 55.1% not seeking for a job. |

In terms of engagement with LinkedIn, there were no significant differences between these two sub-samples in terms of active participation and passive consumption. However, sub-sample 2 had higher perceived profile disclosure than that of sub-sample 1 (difference= 0.429, $p<0.05$). One possible explanation for the higher level of profile disclosure for sub-sample 2 is that, on average, they joined LinkedIn longer than sub-sample 1, and as a result, they disclosed more information over time.

To investigate the possible differences between the two sub-samples, a multi-group analysis (MGA) in SmartPLS was run. MGA analysis enables researchers to have a full picture of heterogeneity effects in their models (Hair et al., 2016). Table 5.25 shows the results of PLS-MGA analysis for two sub-samples. As can be seen in Table 5.25, these two sub-samples do not significantly affect any relationships in the research model.

Table 5.25 PLS-MGA Analysis Results for Two Sub-Samples

| | Path Coefficients Difference Between Two Sub-Samples | P-value |
|---|---|---|
| A_Partici -> Netw_S | 0.057 | 0.681 |
| A_Partici -> Soc_Con | 0.080 | 0.436 |
| Netw_S -> Val_Netw | 0.033 | 0.676 |
| P_Consum -> Netw_S | 0.005 | 0.968 |
| P_Consum -> Soc_Con | 0.108 | 0.340 |
| Pro_Disc -> Netw_S | 0.130 | 0.196 |
| Pro_Disc -> Soc_Con | 0.017 | 0.867 |
| Soc_Con -> Val_Netw | 0.027 | 0.720 |

A_Partici = Active Participation; Netw_S = Network Size; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

### 5.7.2 Assessment of the Effect of Control Variables

Six control variables including age, gender, level of education, immigration status, job seeking status, and LinkedIn membership duration were included in the current study. To ensure consistency and interpretability of between-group comparisons, multicategorical variables including age, level of education, and LinkedIn membership duration were converted to binary variables. To convert each of these multicategorical variables to a binary variable, a couple of one-way ANOVA analysis in SPSS and multi group analysis (MGA) in SmartPLS was run to make sure that only those categories which are not significantly different from each other are merged. Table 5.26 shows the list of all control variables used in this study and their categories. Table 5.27 shows the number of people for each category of control variables.

Table 5.26 Control Variables Groups

| | Category one (Reference) | Category 2 |
|---|---|---|
| Age* | 18-34 years old | 44-54 years old |
| Education* | High school and college diploma | Undergrad and higher |
| Gender | Female | Male |
| Immigration Status | No | Yes |
| Job_Seeking Status | No | Yes |
| LinkedIn Mem_Status* | Two years and less | More than two years |

* converted to a binary variable

Table 5.27 Number of People for Each Category of Control Variables

| | | No. |
|---|---|---|
| Age* | Category 1 | 262 |
| | Category 2 | 108 |
| Education* | Category 1 | 200 |
| | Category 2 | 176 |
| Gender | Category 1 | 236 |
| | Category 2 | 137 |
| Immigration Status | Category 1 | 234 |
| | Category 2 | 136 |
| Job_Seeking Status | Category 1 | 206 |
| | Category 2 | 171 |
| LinkedIn Mem_Status | Category 1 | 138 |
| | Category 2 | 239 |

Effect size analysis using SmartPLS was applied to interpret the potential impacts of control variables. Table 5.28 shows the $f^2$ effect sizes for each control variable in the model. According to Cohen (1988), the effect sizes of 0.02, 0.15, and 0.35 are small, medium, and large, respectively. As a result, as can be seen in Table 5.28, LinkedIn Membership Duration has a small but significant $f^2$ effect size of 0.052. Assuming 0.1 significance level, Age and Education also have small $f^2$ effect sizes.

Table 5.28 Control Variables $f^2$ Effect sizes

| | **Netw_S** | **Soc_Con** | **Val_Netw** |
|---|---|---|---|
| **Age** | 0.007 (0.761) | **0.041 (0.069)** | 0.006 (0.763) |
| **Gender** | 0.004 (0.811) | 0.003 (0.944) | 0.004 (0.857) |
| **Education** | 0.004 (0.702) | 0.012 (0.457) | **0.047 (0.056)** |
| **Immigration Status** | 0.025 (0.178) | 0.010 (0.519) | 0.005 (0.729) |
| **Job Seeking Status** | 0.005 (0.711) | 0.006 (0.686) | 0.003 (0.945) |
| **LinkedIn Membership** | **0.052 (0.004)** | 0.009 (0.486) | 0.009 (0.437) |

Netw_S = Network Size; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

Table 5.29 shows the path coefficients for each control variable. As can be seen, relationships between age and social connectedness, education and networking value, immigration status and network size, and LinkedIn membership and Network size are significant.

Table 5.29 Control Variables Path Coefficients

| | Sample Mean (M) | P Values |
|---|---|---|
| Age -> Netw_S | 0.057 | 0.315 |
| **Age -> Soc_Con** | **0.156** | **0.000** |
| Age -> Val_Netw | -0.045 | 0.286 |
| Education -> Netw_S | -0.031 | 0.609 |
| Education -> Soc_Con | 0.081 | 0.093 |
| **Education -> Val_Netw** | **-0.187** | **0.000** |
| **Emig_Stat -> Netw_S** | **0.137** | **0.006** |
| Emig_Stat -> Soc_Con | -0.063 | 0.125 |
| Emig_Stat -> Val_Netw | 0.044 | 0.314 |
| Gender -> Netw_S | 0.032 | 0.506 |
| Gender -> Soc_Con | -0.011 | 0.742 |
| Gender -> Val_Netw | -0.018 | 0.698 |
| Job_Seeking -> Netw_S | -0.041 | 0.385 |
| Job_Seeking -> Soc_Con | -0.033 | 0.404 |
| Job_Seeking -> Val_Netw | 0.010 | 0.790 |
| **Link_Mem -> Netw_S** | **0.230** | **0.000** |
| Link_Mem -> Soc_Con | -0.070 | 0.119 |
| Link_Mem -> Val_Netw | 0.086 | 0.092 |

A_Partici = Active Participation; Netw_S = Network Size; P_Consum = Passive Consumption; Pro_Dis = Perceived Profile Disclosure; Soc_Con = Perceived Social Connectedness; Val_Netw = Perceived Networking Value

Table 5.30 shows the results of moderation analysis in SEM-PLS by modeling all possible interaction effects between independent and mediator variables and control variables. A two-stage approach was used to create interaction terms. The two-stage approach is preferred, according to Hair et al. (2016), if the objective is whether or not the moderator exerts a significant effect on the relationship.

Table 5.30 Moderation Analysis Results

| No. | Independent Variable | Dependent Variable | Moderator | Effect Size | Confidence Interval | Significant |
|---|---|---|---|---|---|---|
| 1 | Perceived Profile Disclosure | Perceived Social Connectedness | Job Seeking | 0.087 | 0.008 – 0.165 | Yes |
| 2 | Active Participation | Perceived Social Connectedness | Gender | 0.067 | 0.009 – 0.129 | Yes |
| 3 | Perceived Profile Disclosure | Network Size | Job Seeking | -0.092 | -0.167 – -0.011 | Yes |
| 4 | Perceived Social Connectedness | Perceived Networking Value | Gender | 0.093 | 0.013 – 0.176 | Yes |

Based on moderation analysis results shown in Table 5.30, it can be concluded that:

- (1) The strength of the relationship between perceived profile disclosure and perceived social connectedness is significantly different between non-job seekers and job seekers in a way that the relationship is stronger for job seekers (Figure 5.3).
- (2) The strength of the relationship between active participation and perceived social connectedness is significantly different between females and males in a way that the relationship is stronger for males (Figure 5.4).
- (3) The strength of the relationship between perceived profile disclosure and network size is significantly different between non-job seekers and job seekers in a way that the relationship is stronger for non-job seekers (Figure 5.5).

- (4) The strength of the relationship between Perceived social connectedness and perceived networking value is significantly different between females and males in a way that the relationship is stronger for males (Figure 5.6).

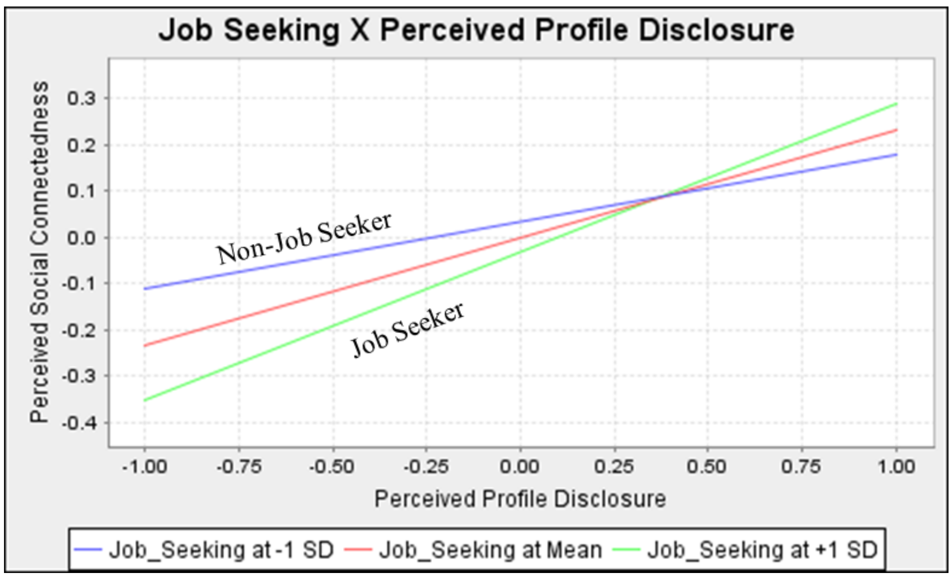



Figure 5.3 Moderating Effect of Job Seeking on the Relationship Between Perceived Profile Disclosure and Social Connectedness

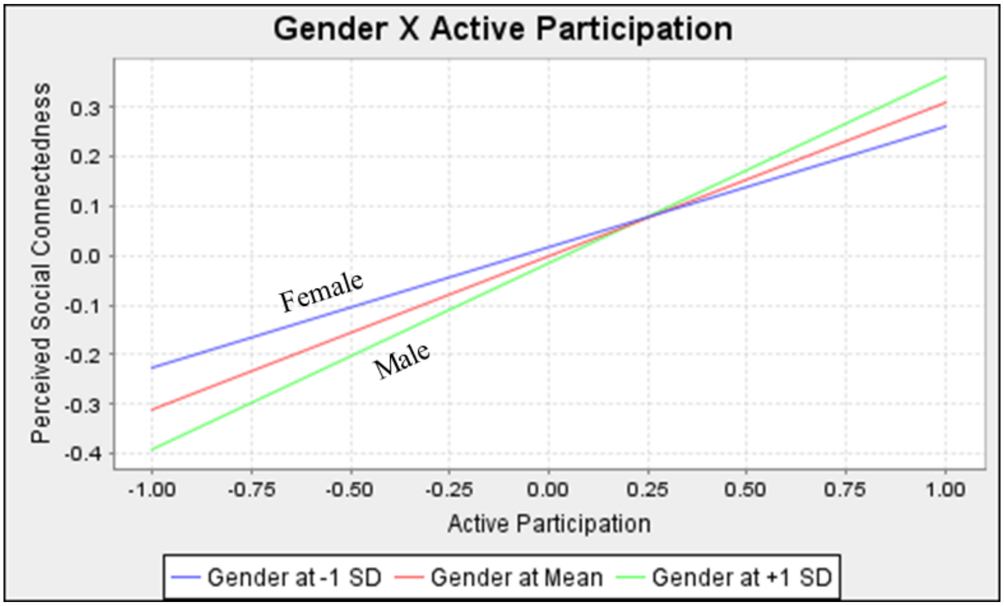



Figure 5.4 Moderating Effect of Gender on the Relationship Between Active Participation and Perceived Social Connectedness

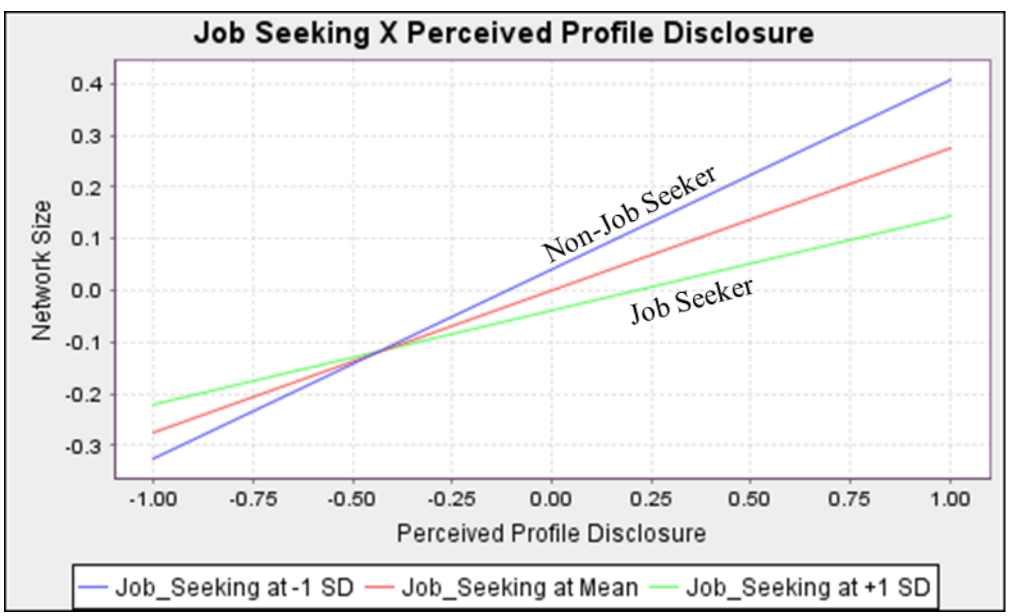



Figure 5.5 Moderating Effect of Job Seeking on the Relationship Between Perceived Profile Disclosure and Network Size

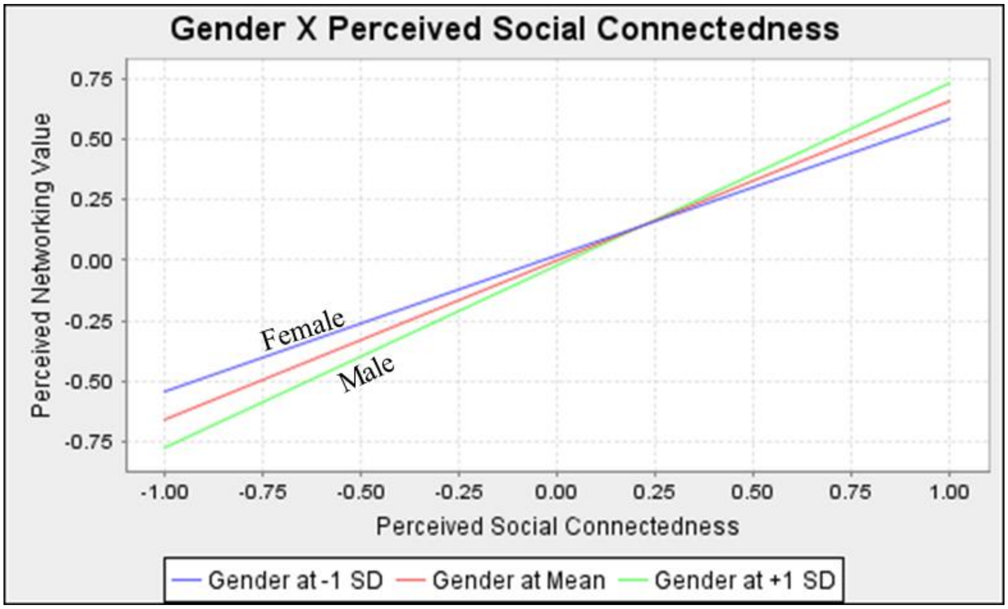



Figure 5.6 Moderating Effect of Gender on the Relationship Between Perceived Social Connectedness and Perceived Networking Value

### 5.8 Perceived Profile Disclosure and Profile Features on LinkedIn

As it was discussed earlier, perceived profile disclosure aims to measure individuals' own evaluation of how much, and how clearly they disclose their personal and professional information through profile fields of their P-SNS account. As such, this construct measures both depth and breath of information disclosed by a user (e.g., I have a detailed profile on LinkedIn; I have a comprehensive profile on LinkedIn) as well as how clear it is to determine his/her skills and competencies (e.g., from my LinkedIn profile it would be easy to find out my skills and competencies).

However, perception of profile disclosure may differ from actual profile disclosure. As such, participants were asked to answer some questions regarding their profiles. Appendix-2 shows the list of such questions. On LinkedIn, users can disclose their personal and professional information through various fields such as photo, education, experience, headline, summary, skills, etc. Previous research showed the importance of 11 profile fields on LinkedIn including photo, education, industry, job position, summary, headline, skills, contact, external links, location, recommendation (Chiang & Suen, 2015; Zide et al., 2014). The number of professional groups a user belongs to was added as it may indicate social credentials and recognitions. Table 5.31 shows the results of the Profile descriptive statistics for the research sample.

To measure the extent to which users complete their profiles based on the above 12 features, a composite formative variable named profile completeness was developed. It is important to note the difference between composite and causal formative variables. In composite formative variables, all indicators combine in a linear way to form a variate. In contrast, in causal formative variables, indicators do not form the latent variable, but they cause it (Hair et al., 2016). In this research, all 12 features were combined in a linear way to measure the extent to which users completed their profiles. To measure the extent of the relationship between profile completeness and perceived profile disclosure, a PLS model was used. Figure 5.7 shows the results of the PLS model.

Table 5.31 Descriptive Statistics for Profile Features on LinkedIn

| No. | LinkedIn Profile Feature | Category | Frequency (%) |
|---|---|---|---|
| 1 | Photo | Yes | 64.7 |
| | | No | 35.3 |
| 2 | Headline | Yes | 55.7 |
| | | No | 44.3 |
| 3 | External Links | Yes | 43.5 |
| | | No | 56.5 |
| 4 | Education | Yes | 69.0 |
| | | No | 31.0 |
| 5 | Industry | Yes | 67.9 |
| | | No | 32.1 |
| 6 | Location | Yes | 72.4 |
| | | No | 27.6 |
| 7 | Member of Groups | 0 | 23.9 |
| | | 1-10 | 60.7 |
| | | 11-20 | 10.6 |
| | | 21-30 | 3.2 |
| | | 31-50 | 1.3 |
| 8 | Number of Skills Reported | 1-10 | 40.8 |
| | | 11-20 | 34.5 |
| | | 21-30 | 12.7 |
| | | 31-40 | 3.4 |
| | | 41-50 | 3.7 |
| 9 | Profile Summary | I have no Summary | 27.1 |
| | | Somewhat (1 short paragraph, mostly historical info) | 35.8 |
| | | Pretty good (1-3 short paragraphs, current business highlighted) | 28.4 |
| | | Excellent (close to 2,000 characters, keywords, clear explanation of what I've accomplished, what I do, and who I would like to meet) | 5.6 |
| 10 | Job Position | Yes | 69.2 |
| | | No | 30.0 |
| 11 | Recommendation | Yes | 50.9 |
| | | No | 47.5 |
| 12 | Contact Info. | Yes | 58.4 |
| | | No | 41.4 |

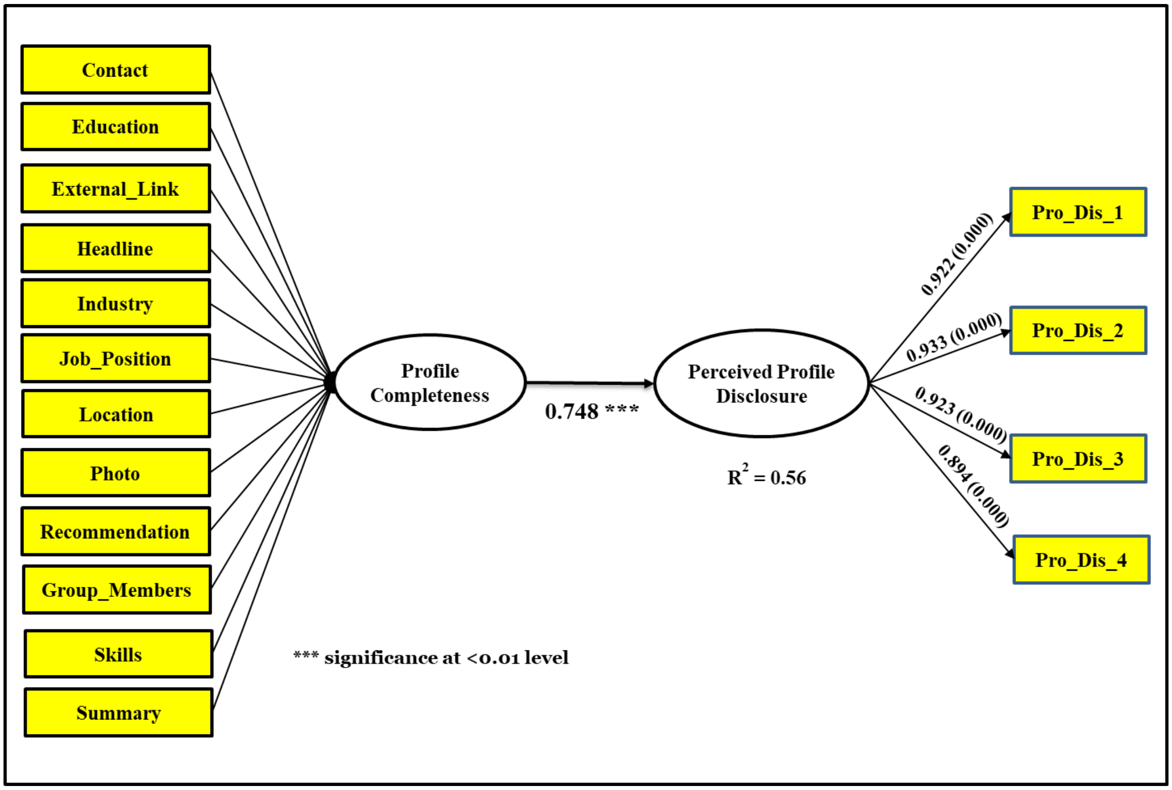



Figure 5.7 PLS Model for Profile Disclosure

As shown, the path coefficient between profile completeness and perceived profile disclosure is 0.748 ($p < 0.000$) which is above the threshold of 0.70 (Hair et al., 2016). Also, the model $R^2$ is 0.56 which is above the threshold of 0.50 specified by Hair et al. (2016). Table 5.32 shows the results of indicators' weights and loadings on profile completeness. In line with the procedure proposed by Hair et al. (2016), shown in Figure 5.8, all indicators were kept.

Table 5.32 Indicators' Weights and Loadings on Profile Completeness

| Formative Indicators | Outer Weight | P-Value | Outer Loadings | P-Value |
|---|---|---|---|---|
| Education | 0.403 | 0.000 | 0.674 | 0.000 |
| Groups Membership | 0.112 | 0.032 | 0.576 | 0.000 |
| External Link | 0.170 | 0.002 | 0.187 | 0.006 |
| Contact | 0.115 | 0.071 | 0.491 | 0.000 |
| Headline | 0.101 | 0.050 | 0.360 | 0.000 |
| Industry | -0.057 | 0.497 | 0.503 | 0.000 |
| Job Position | 0.096 | 0.302 | 0.575 | 0.000 |
| Location | 0.071 | 0.320 | 0.539 | 0.000 |
| Photo | 0.064 | 0.371 | 0.681 | 0.000 |
| Recommendation | 0.135 | 0.007 | 0.203 | 0.002 |
| Skills | 0.275 | 0.000 | 0.554 | 0.000 |
| Summary | 0.372 | 0.000 | 0.654 | 0.000 |

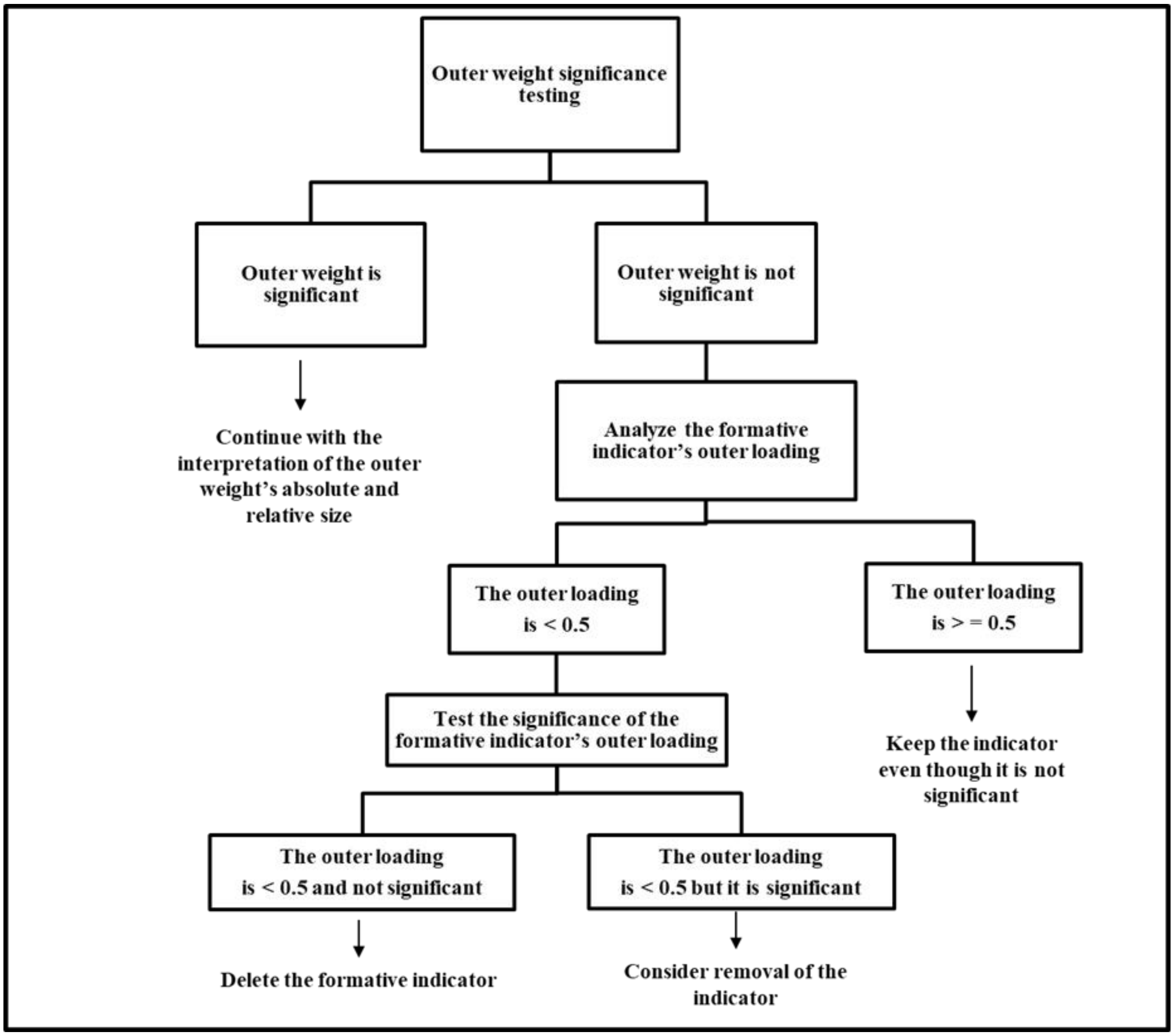



Figure 5.8 Decision-Making Process for Keeping or Deleting Formative Indicators (Hair et al., 2016, p.150)

Table 5.33 shows the relative importance of profile completeness indicators based on their outer weights. As can be seen, education, summary, and skills are the most important indicators.

Table 5.33 Relative Importance of Profile Features

| Rank | LinkedIn Profile Feature |
|---|---|
| **1** | Education |
| **2** | Summary |
| **3** | Skills |
| **4** | External Link |
| **5** | Recommendation |
| **6** | Contact |
| **7** | Groups Membership |
| **8** | Headline |
| **9** | Job Position |
| **10** | Location |
| **11** | Photo |
| **12** | Industry |

### 5.9 Open-ended Question Results

Earlier in this thesis, the important role of purpose of actions in the social capital formation process was discussed. According to Lin (2008), the purpose of actions – instrumental (e.g., secure a job) vs. expressive (e.g., emotional support for mental health) – affects the social network and results in different social capital outcomes. As such, an open-ended question was asked from survey participants: “why you mainly use LinkedIn? In addition, if you have any comments about how useful LinkedIn is for your networking efforts, please mention”.

In total, 307 participants answered the open-ended question. 26 responses were removed because they were not relevant to the question or answered ‘none’, ‘no comment’, or ‘ I don’t know’. Therefore, 281 responses were considered for further analysis. Content analysis technique was used to analyze the data. Content analysis is a quantitative approach to analyze the content of qualitative data. It involves coding content to pre-determined categories and then using quantitative techniques to analyze the coding (Myers, 2013). After careful consideration, five categories were chosen to code the data: maintaining relationships, building new connections, self-presentation, job search, and general information and news. These five categories are in line with the extant literature on SNSs (Ellison, Vitak, & Gray, 2014; Zide et al., 2014). All 281 responses were read and coded based on these five categories. 38 percent of responses were coded with two categories and 3 percent were coded with three categories. Table 5.34 shows the frequency of each category. Building new connections, maintaining relationships, and self-presentation, which are central to professional networking, comprise more than 63 percent of reasons to use LinkedIn. Tables 5.35 to 5.39 show a sample of participants' responses for each category.

Table 5.34 Frequency of Categories Assigned to Open-Ended Question Responses

| No | Category | Frequency |
|---|---|---|
| **1** | Maintaining relationships | 102 |
| **2** | building new connections | 116 |
| **3** | self-presentation | 32 |
| **4** | Job search | 132 |
| **5** | general information and news | 14 |

Table 5.35 Participants' Responses for Job Search

| No | Participant' Response |
|---|---|
| 1 | I use LinkedIn to increase my chance of getting a job in case my hiring managers look for it. |
| 2 | For job searches |
| 3 | To look for job opportunities |
| 4 | To browse job openings and to research job requirements and duties for different organizations |
| 5 | for career purposes |
| 6 | To find new/interesting jobs in my field |
| 7 | Job hunt |
| 8 | I though I could find a job via LinkedIn |
| 9 | Looking for better opportunities |
| 10 | for job market |
| 11 | I use it for future employment opportunities. |
| 12 | to look for internships |

Table 5.36 Participants' Responses for Maintaining Relationships

| No | **Participant' Response** |
|---|---|
| 1 | keep connected |
| 2 | Maintain connections with people that I have worked with (school and jobs). |
| 3 | To keep in touch with professional acquaintances |
| 4 | stay in contact with people I know |
| 5 | staying connected with people I meet at networking sessions and having the ability to stay in the loop with a professional network |
| 6 | to keep business connections alive. |
| 7 | Maintain work and professional connections, share news stories and information with community, ensure I am relevant as a source of good information. |
| 8 | To keep business connections, and keep in touch with old colleagues. |
| 9 | Stay in touch with my friends from University |

Table 5.37 Participants' Responses for Building New Connections

| No | **Participant' Response** |
|---|---|
| 1 | to make connections |
| 2 | I use LinkedIn because it is a great tool to meet professionals in the areas of business which I am trying to break in to. I have learned a lot about these said areas from people I would not have met if it was not for LinkedIn. |
| 3 | Build connections for future employment |
| 4 | for networking to the right job |
| 5 | i use LinkedIn so I can grow my professional network online and receive job updates. |
| 6 | To be able to connect with people in my field of research. |
| 7 | make connections and find jobs when I'm in need of one |
| 8 | I used LinkedIn to connect with employers and keep up to date with what's going on in the world. |
| 9 | To gain connections and to network with people. And also, after networking sessions to follow up as many people use LinkedIn with regards to communication instead of emails. |

Table 5.38 Participants' Responses for Self-Presentation

| No | Participant' Response |
|---|---|
| 1 | To build a brand of myself to my collogues and the profession I am in |
| 2 | To have a professional profile online, also because I am in business and most business students use it. |
| 3 | To describe myself to potential employers |
| 4 | Keep my name out there, connect to high profile individuals, share pertinent business information. |
| 5 | I use it as a resume, and to connect with others. |
| 6 | Mainly use LinkedIn to inform my connections of my skills and abilities in hopes to find a successful job when I graduate. Also, I find out through connections if there is a vacancy in jobs. |
| 7 | I use LinkedIn to coherently display my experiences and capabilities. I find it a much more organized and professional way to showcase your professional information. |
| 8 | Display my profile and accomplishments and connect with like minded people. |

Table 5.39 Participants' Responses for General Information and News

| No | Participant' Response |
|---|---|
| 1 | Get updated with current industry trends from content posted/recommended by others, connections' recent news, and work opportunities. |
| 2 | to stay up to date on trends in my field and in the world |
| 3 | updates on my field |
| 4 | I mainly use LinkedIn to read about interesting news about tech and business. I also enjoy reading articles and/or captions of stories and experiences that founders and CEOs of companies share. |
| 5 | learn about new developments and news in general and make connections |
| 6 | news |

# Chapter 6 : Discussion and Conclusion

This chapter presents the answers to the research questions outlined in the introduction section of this thesis based on the results of the empirical study presented in chapter 5. Both academic and practical contributions are explored, followed by research limitations. Lastly, suggestions for future research and a conclusion are provided.

## 6.1 Research Questions and Main Findings

As introduced in section 1.1, this study aims to answer the following research questions:

(1) How does users' profile disclosure lead to accruing and developing social capital on P-SNSs?

(2) How do users' actions on P-SNSs such as active participation and passive consumption lead to accruing and developing social capital on P-SNSs?

To answer the above research questions, a research model was developed based on the theoretical frameworks of Social Network Analysis, Social Media Analysis, and Social Capital Theory. This model proposes that SNS users' actions such as disclosing their personal information through their profiles, active participation, and passive consumption can lead to developing sources of social capital (operationalized as network size, and social connectedness) which, in turn, will provide them networking value.

The empirical study presented in chapter 5 has four main findings:

- (1) P-SNS users' actions (perceived profile disclosure, active participation, and passive consumption) have significant positive effects on perceived social connectedness (H1a, H1b, 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 have any effect on network size (H2b not supported)
- (4) network size on P-SNSs does not have a significant effect on perceived networking value (H5 not supported)

In summary, this research results indicate that the more individuals perform various actions on P-SNSs, the more they perceive networking value if they feel more connected to their social networks on these sites. Also, while P-SNS users' actions such as profile disclosure and passive consumption can lead to increased network size, the larger network size does not necessarily lead to increased perceived networking value.

In the remainder of this section, each of the above four main findings is discussed in detail.

### 6.1.1 P-SNS Users' Actions and Perceived Social connectedness (Main Finding-1):

This research results show that active participation (0.331, $p<0.000$) followed by passive consumption (0.249, $p<0.000$) and perceived profile disclosure (0.238, $p<0.000$) have significant positive effects on perceived social connectedness. These findings are supported by the extant literature (Grieve et al., 2013; Köbler et al., 2010; R. Linn & Utz, 2017). Based on the extant literature on SNSs, individuals engage with SNSs mainly in the form of active participation (e.g., like, comment, post/share, etc.) or passive consumption (e.g., follow the news of connections, look through the news-feed, etc.) to primarily maintain their relationships with others in their social networks (Ellison & Vitak, 2015; Utz & Breuer, 2019). This leads to specific relational outcomes such as perceived relational closeness (Burke & Kraut, 2014; Ellison & Vitak, 2015; Koroleva et al., 2011; Vitak, 2012). The relational closeness can be increased continuously as people continue engaging with SNSs (Vitak, 2012). An increased sense of relational closeness can eventually lead to enhancing the quality of relationships between an individual and his/her social network and forming a feeling of connection or belongness toward others in his network (Nadkarni & Hofmann, 2012; Vitak, 2012). This feeling of connection, according to Lin (2008), 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 (Kawachi et al., 2008).

This research results also show that active participation has a stronger effect on perceived social connectedness than passive consumption does. An individual's active participation in SNSs through liking, commenting, or sharing others' posts can be perceived as signals of attention. Also, it can imply his/her social presence. The feeling of getting others' attention, as well as awareness of the presence of others, create an environment in which reciprocal relationships are strengthened, and as a result, a sense of connectivity can be boosted (Dey & de Guzman, 2006; Ellison & Vitak, 2015). In contrast, passive consumption cannot create such an environment because it cannot establish reciprocity (Alloway & Alloway, 2012). Therefore, the effect of passive consumption on perceived social connectedness is mainly limited to the extent to which it can create relational closeness between a user and its network, as described earlier.

Based on this research results, perceived profile disclosure also positively affects perceived social connectedness. An individual's perceived profile disclosure on SNSs, according to this research results, is highly correlated to the extent to which he/she discloses his/her personal and professional information through profile fields of his account. An increase in depth and breadth of information shared by an SNS user through his profile fields can positively affect his perceived social connectedness toward his network in two ways: First, it makes network members become more trusting of each other as they can establish more common grounds with each other. This enhanced trust, in turn, can lead to facilitating relationship development and increasing the feeling of connection among network members (Sturgis, Patulny, Allum, & Buscha, 2012). This can explain why YouTube users tend to report lower levels of social connectedness than Facebook users. Profile features in YouTube, compared to Facebook, is limited and may not be sufficient for establishing social connectedness as that of Facebook (Alloway & Alloway, 2012).

Second, disclosing more personal and professional information on SNSs may increase users' engagement with these sites (e.g., spending more time to update and improve users' profile) and also result in more interactions with other members (e.g., asking for recommendations, endorsing skills, etc.) (Alloway & Alloway, 2012). However, SNS users do not change or update their profile information or ask for recommendations or endorsement as frequently as they actively participate (like, comment, or share a post) or passively consume (follow or look through news-feed) on these sites (Ellison & Vitak, 2015). Therefore, a lower level of social connectedness resulted from such activities (which are derived from profile disclosure) than active participation and passive consumption is expected. Comparing SNS platforms, a higher level of social connectedness on P-SNSs (LinkedIn) than S-SNSs (Facebook) is expected mainly because one's profile specifically in P-SNSs is the key means for fulfilling self-presentation purposes, so users tend to more frequently update and improve their profiles on P-SNSs and as a result, spend more time on their profiles on these sites. They also tend to reveal more information via their P-SNS profiles to make sure that their profiles present them in the best way. Although perceived profile disclosure significantly affects perceived social connectedness through the aforementioned two ways, this research results show that perceived profile disclosure has less effect on perceived social connectedness than active participation and passive consumption do.

This study also found that the strength of the relationship between perceived profile disclosure and perceived social connectedness is significantly different between non-job seekers and job seekers in a way that the relationship is stronger for job seekers. It can be argued that because job-seekers actively look for a job, they are more engaged with SNSs than non-job seekers. More engagement can help job seekers enhance the utilization of their profiles (e.g., spend more time to update and improve their profiles) and as a result, the effect of profile disclosure on perceived social connectedness becomes stronger.

Additionally, based on this research results, the strength of the relationship between active participation and perceived social connectedness is significantly different between females and males in a way that the relationship is stronger for males. This finding is in line with the extant literature. Vitak (2012) found that men were more likely than women to report that Facebook use had a positive impact on their relational closeness. Other studies found that men are more likely to look at other people's profiles to find friends and they are more interested in meeting new people with similar interests on SNSs than women (Haferkamp, Eimler, Papadakis, & Kruck, 2012; Tufekci, 2008).

### 6.1.2 Perceived Social connectedness and Perceived Networking Value (Main Finding-2):

This study found that perceived social connectedness on P-SNSs has a significant positive effect (0.671, $p<0.000$) on perceived networking value on these sites. This is in line with the extant literature. The extant literature on social connectedness supports the association between social connectedness and various social capital outcomes such as networking value, lower depression, life satisfaction, etc. (Ahn & Shin, 2013; Grieve et al., 2013; Koroleva et al., 2011; S. Stone & Logan, 2018). Social connectedness represents one's overall perception of quality of relationships with his/her network. As a source of social capital, one's social connectedness to his/her network indicates that how much he/she feels that he/she can get support from his/her network. This feeling can lead to forming deeper social ties such as the feeling of bonding to a network (Lin, 2008). Without such a feeling of connectedness, even if an individual possess valuable resources in his/her network, it is less likely that he/she feels that he/she can mobilize such resources and gain benefits from them. It lowers his/her perceived networking value from his/her SNS network and can even lead to less engagement with these sites.

This research results show that the strength of the relationship between perceived social connectedness and perceived networking value is significantly different between females and males in a way that the relationship is stronger for males. A study by LinkedIn (2019) shows that men are more likely to ask for a referral on LinkedIn than women. There is a 68% likelihood that men ask for a referral before applying to a job, compared to women's 32% (LinkedIn Corporate Communications Team, 2019). Although asking for referrals is only one item out of six items that were used in this study to measure perceived networking value, it may partially indicate that men perceive higher networking value than women on LinkedIn.

### 6.1.3 P-SNS Users' Actions and Network Size (Main Finding-3):

This research results show that while perceived profile disclosure and passive consumption have significant positive effects on network size, active participation does not have any effect on network size. These findings are in line with Lampe et al. (2007) findings that there is a significant association between completing some Facebook profile features and number of friends. Similarly, Lin et al. (2014) found that there is a significant association between network size and need for impression management. It may look surprising that one's active participation on SNSs does not affect his/her 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, it is first needed to examine carefully at how active participation may lead to an increased network size on SNS platforms.

Active participation as conceptualized in this study includes three main actions: like others' posts; comment under others' posts; or share/reshare something on your wall. In general, one's active participation can lead to an increased network size if (1) he/she will be seen by his/her extended network (connections of one's connections) on SNSs, and then (2) he/she receives a connection request by his/her extended network, and he/she accepts it. As such, it is less likely that by liking or commenting, one will be seen by his/her extended network on SNSs because when an individual likes or comments under connections' posts, only his/her connections can see his/her likes or comments, not his/her extended network. However, when an individual shares/reshares a post on his/her wall, and his/her post receives some likes and comments, depending on his/her visibility or privacy setting, his/her extended network can see his/her post. Then, he/she may receive some connection requests from his/her extended network, which may be accepted or rejected by him/her. Therefore, if an SNS user does not share/reshare a post, it is less likely that his/her network is expanded by his/her active participation. Even if he/she does so, considering all probabilities (the probability that his/her post receives likes or comments, the probability that he/she receives connection requests, and the probability that he/she accepts such requests), unless he/she does it with high frequency, the chance that sharing a post leads to a larger network size remains low. In research sample, approximately 80 percent of participants share a post a few times in a year or almost monthly, and less than eight percent share a post every week. The latter figure for the general LinkedIn population is only one percent (Osman, 2019). Because sharing a post on P-SNSs is not frequent, and other types of active participation such as liking and commenting as explained above have no or little effect on network size, it can arguably be concluded that, in line with this research result, active participation tends to have no significant impact on network size.

The mechanism through which one's network size is expanded is different for passive consumption and profile disclosure. Regarding passive consumption, an SNS user reads and follows other's posts including his/her extended network's posts (given that they received likes and comments by his/her connections), and then he/she may send a connection request which may be accepted by the receiver. In the research sample, approximately 60 percent of participants read, follow, or click on the content shared by connections every 2-3 weeks. On average, in the research sample, the frequency of passive consumption is higher than that of active participation (every 2-3 weeks for passive consumption versus a few times in a year to monthly for active participation). This may explain why, unlike active participation, passive consumption significantly affects network size.

The way that an individual can add new people to his/her network through his/her profile disclosure is completely different than that of active participation and passive consumption. On LinkedIn, the "People You May Know" feature suggests LinkedIn members to a user to connect with. These suggestions are based on factors such as similarity in profile information and experiences, working at the same company or industry, or attending the same school. As such, the more a user discloses his/her personal and professional information on LinkedIn, the more he/she receives such suggestions even if he/she does not spend much time following other people on LinkedIn. This is an automated and effective tool on LinkedIn designed to help expand one's network.

This research results show that the strength of the relationship between perceived profile disclosure and network size is significantly different between non-job seekers and job seekers in a way that the relationship is stronger for non-job seekers. One possible explanation for such a finding is that job seekers are in the process of building their networks and, on average, have less network size than non-job seekers. In other words, non-job seekers already benefited from their profiles in terms of expanding their networks.

### 6.1.4 Network Size and Perceived Networking Value (Main Finding-4):

Network size on SNSs does not have a significant effect on perceived networking value. It seems surprising that larger network size does not lead to an increased perception of networking value. However, the extant literature on the effect of network size on social capital outcomes is contradictory. While some studies such as Burke et al. (2010) or 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 relationships between network size and social capital outcomes. For example, Ellison et al. (2011) found that the number of actual friends (a percentage of total number of friends) rather than the total number of friends has a significant effect on bridging social capital. Even for those considered to be actual friends, the effect diminishes above the range of 400-500 (Ellison, Steinfield, & Lampe, 2011). Similarly, 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 (Tang & Lee, 2013). In subsequent research on the effects of networking on LinkedIn, Utz (2019) found that only total number of weak ties (not strong ties) is positively related to informational benefits on LinkedIn (Utz & Breuer, 2019)

In this research, perceived networking value was conceptualized based on four social capital benefits proposed by Lin (2008): information; influence; social credential; and reinforcement. If only the information dimension items (3 items) are kept and the other three items related to other dimensions are removed, the relationship between network size and the modified perceived networking value construct (which meets all reliability and validity criteria) becomes significant, although the model's $R^2$ drops significantly. Inversely, if only influence, social credential, and reinforcement dimensions are kept and information dimension items are removed, the relationship between network size and new modified perceived networking value (which meets all reliability and validity criteria) becomes not only insignificant but also worse in terms of effect size. However, the model's $R^2$ change is very small. Table 6.1 summarizes these findings.

Table 6.1 Research Model Results based on Changes on Perceived Networking Value

| **Model** | **Network size-Perceived Networking Value** | **Perceived Social Connectedness - Perceived Networking Value** | **Model $R^2$** |
|---|---|---|---|
| Original | 0.063 (0.097) | 0.670 (0.000) | 0.459 |
| Perceived Networking Value Construct with only Information Dimension Items | 0.090 (0.040) | 0.522 (0.000) | 0.301 |
| Perceived Networking Value Construct with only Non-Information Dimensions Items (Influence, Social Credential, and Reinforcement) | 0.034 (0.426) | 0.659 (0.000) | 0.431 |

These findings show that non-information dimensions of perceived networking value such as influence, social credential, and reinforcement are highly related to perceived social connectedness and not related to total network size. In contrast, the information dimension of perceived networking value is positively related to total network size and less to perceived social connectedness. Also, extending Tang & Lee (2013) conclusion, this research findings suggest that perceived social connectedness rather than network size can lead to non-informational social capital benefits.

In sum, the following insights from this study are gained:

- Although active participation in P-SNSs is the most important factor in creating a sense of connectedness on these sites, it does not affect the network size. It is a surprising finding which extends the literature on SNSs.
- Users' profile on P-SNSs play an important role in their network size. The more P-SNS users disclose their personal and professional information on their profile fields, the larger network size they will have.
- Perceived social connectedness as a source of social capital is the key mediator between users' actions such as passive consumption and active participation and social capital benefits they can gain from these sites.
- Network Size is significantly associated with the information dimension of perceived networking value.
- Other than job search, building new connections, and maintaining relationships are the primary motivations for using P-SNSs.

## 6.2 Research Contribution

The contributions of the current research in terms of theory and practice are outlined in the following sections. It is believed that this research on P-SNSs can be of interest to both academics in the discipline of IS as well as business practitioners.

### 6.2.1 Theoretical Contributions

From a theoretical perspective, this research offers the following contributions:

- In general, P-SNSs are under-researched in IS. Therefore, by doing this research on LinkedIn as one of the most widespread P-SNS platforms, and given the fact that P-SNS platforms have distinct differences from S-SNS platforms (e.g., profile features), this research advances our knowledge of how individuals interact with these platforms.
- This research proposes and validates a model of social capital formation for the context of P-SNS. Surprisingly, there are only a few studies that investigate the process of social capital formation on these sites. Past studies (e.g., Ellison et al. 2014) have mainly investigated the relationships between SNS users' specific activities and traditional bridging and bonding social capital. However, they have not investigated 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. According to Lin (2008), social capital sources should be considered as necessary and important antecedents exogenous to social capital outcomes. As such, it is believed that this study enhances the depth and breadth of our understanding of how social capital forms in SNSs.
- By including the perceived profile disclosure construct in the research model, 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. As such, this study provides the opportunity to analyse the relative importance of each of these constructs in this process.

- By integrating the theoretical frameworks of Social Network Analysis, Social Media Analysis, and Social Capital Theory, this research presents a comprehensive conceptual model of social capital formation in the P-SNS context which can be served as a basis for future empirical studies in this domain.

### 6.2.2 Practical Contributions

This study targets different audiences, such as individuals interested in extending their networks (e.g., job seekers), policy makers, 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 the following contributions:

- According to Utz (2019), LinkedIn is widely used among professionals who tend to do networking for various reasons. Also, senior college and university students and fresh graduates can use P-SNSs to expand their social networks and secure their first jobs. By understanding which factors significantly influence the social capital formation 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.
- The results of this study show that P-SNS platforms can potentially help people develop and accrue social capital more easily and with lower costs. As such, the results of this study can be served as evidence for policy makers to show that increased 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 can lower costs and improve the effectiveness of such services.

- 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 improve their networking services to their users. For example, P-SNS providers can design new profile features that allow users to showcase their social credentials to their connections. This can also enhance the self-presentation affordances of P-SNS platforms. As another example, due to the importance of referrals in networking, P-SNS providers can design a mechanism that makes the referral process easier for job seekers on these sites.

## 6.3 Research Limitations

Any empirical investigation has its own limitations that should be considered. The following limitations in this study are acknowledged:

First, as this research study is cross-sectional, a definitive causal relationship between independent and dependant variables cannot be drawn. For example, it is ultimately unclear whether an increased sense of connectivity in an SNS user is formed because he/she discloses more information on his/her profile, or he/she discloses more information on his/her profile because he/she feels more connected to his/her social network. However, previous longitudinal studies in this domain support the causality relationship between actions and social capital benefits.

Second, using self-reported and perception measures rather than actual behaviour is another limitation of this study. Although analyses showed that Common Method Variance is not likely to be an issue in this investigation, it is 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.

Third, the generalizability of findings in this study is limited to the Canadian population. It is mainly because patterns of SNS use and self-disclosure behaviour could be quite different in other countries such as European or Asian countries.

Forth, with regards to the qualitative analysis (for the open-ended survey question), no inter-coder reliability testing was performed. Therefore, the results of the content analysis is soley based on the researcher's coding. However, as all comments provided by participants were short and to the point, the lack of inter-coder reliability testing is not a major threat to the validity of the content analysis findings.

Fifth, due to demographic characteristics of the research sample, a potential gender bias may exist in the research results.

Finally, due to significant differences between SNS platforms, the results of this study may only be generalized to P-SNS platforms.

### 6.4 Future Research Suggestions

While this research provides an important step in understanding 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. However, the current measures of network compositional quality (e.g., the name generator or position generator) may not be valid and reliable in the SNS context due to the fact that SNSs afford users large network size which makes it difficult for them to estimate accurately the status of their networks (Lu & Hampton, 2017). This is even more problematic when using an online survey as respondents may struggle with a complex and burdensome questionnaire (Vehovar, Lozar Manfreda, Koren, & Hlebec, 2008). As such, the researcher believes that future research should be more focused on developing new scales to measure network compositional quality in the SNS context.
- Due to 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. Selecting more restricting choices in the privacy settings of an SNS (e.g., setting "who can see your posts" to "only connections") can reduce one's visibility on these sites. This may decrease one's access to more information, opportunities, and valuable resources. To the best of my knowledge, no empirical study has investigated

the impact of privacy settings on the social capital formation process in the P-SNS context.

- Future work with longitudinal data could inform our understanding of the directionality of relationships in the research model.
- More research needs to be done on various P-SNS platforms with different populations such as XING, Udyomitra, etc. to help us expand knowledge of social capital formation process on SNSs. The context of these populations could impact this process.
- As shown in the proposed conceptual model (page 52), social media affordances are antecedents to the social capital formation process. It may be valuable to investigate the relative importance of each of these affordances on social capital sources and outcomes in future research.
- Analysis of the open-ended survey question revealed five user group categories (section 5.9). Future research can further explore these user groups and the validated research model could be examined for generalizability across these categories.

## 6.5 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 professionally-oriented social network sites (P-SNSs) such as LinkedIn. Based on the theoretical frameworks of Social Network Analysis, Social Media Analysis, and Social Capital Theory, my research model proposes 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 (including network size, and social connectedness) which in turn will provide them valuable benefits (networking value).

To validate the proposed research model, a quantitative research methodology was used. An online survey was designed to measure the constructs in the research model. Participants were recruited from the target population at Ryerson and McMaster Universities as well as through Qualtrics, a research service firm. The analysis of 377 participants revealed that (1) SNS users' actions (perceived profile disclosure, active participation, and passive consumption) have significant positive effects on perceived social connectedness; (2) perceived social connectedness on 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 SNSs does not have a significant effect on perceived networking value.

Overall, this investigation advances the depth and breadth of our understanding of how social capital forms in social network sites, specifically professionally-oriented social network sites. In addition, by including a perceived profile disclosure construct in the research model, to the best of our knowledge, this is the first study in the P-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. Moreover, this study targets different audiences, such as individuals interested in extending their networks (e.g., job seekers), policy makers, 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.

# References

Abeele, M. Vanden, Antheunis, M., Pollmann, M. M., Schouten, A. P., Liebrecht, C. C., Van Der Wijst, P. J., & Maes, F. A. (2018). ' Social Capital? A Replication of Ellison, Steinfield, and Lampe's (2007) Study Using the Original and More Recent Measures of Facebook Use and Social Capital. *Communication Studies*, *69*(3), 272–282.

Adamic, L., & Adar, E. (2005). How to search a social network. *Social Networks*, *27*(3), 187–203.

Adams, C. (2011). Social networking and extending social capacity. In *32nd International Conference on Information Systems, Shanghai, China.* (p. 5).

Ahn, D., & Shin, D. (2013). Is the social use of media for seeking connectedness or for avoiding social isolation? Mechanisms underlying media use and subjective well-being. *Computers in Human Behavior*, *29*(6), 2453–2462.

Alhabash, S., & Ma, M. (2017). A Tale of Four Platforms: Motivations and Uses of Facebook, Twitter, Instagram, and Snapchat Among College Students? *Social Media + Society*, *3*(1), 205630511769154.

Allen, K., Ryan, T., Gray, D., McInerney, D. M., & Waters, L. (2014). Social media use and social connectedness in adolescents: The positives and the potential pitfalls. *The Educational and Developmental Psychologist*, *31*(1), 18–31.

Alloway, T., & Alloway, R. (2012). The impact of engagement with social networking sites (SNSs) on cognitive skills. *Computers in Human Behavior*, *28*(5), 1748–1754.

Alloway, T., Horton, J., Alloway, R., & Dawson, C. (2013). Social networking sites and cognitive abilities: Do they make you smarter? *Computers & Education*, *63*, 10–16.

Apptopia.com. (2019). Apptopia|our-data. Retrieved from https://apptopia.com/our-data

Ashuri, T., Dvir-Gvisman, S., & Halperin, R. (2018). Watching Me Watching You: How Observational Learning Affects Self-disclosure on Social Network Sites? *Journal of Computer-Mediated Communication*, *23*(1), 34–68.

Atkin, R. (1977). *Combinatorial Connectivities in Social Systems: an application of simplicial complex structures to the study of large organizations*. *Birkhauser* (Vol. 34).

Becker, J., Rai, A., Ringle, C., & Völckner, F. (2013). Discovering unobserved heterogeneity in structural equation models to avert validity threats. *MIS Quarterly*, *37*(3), 665–694.

Berger, K., Klier, J., Klier, M., & Probst, F. (2014). A review of information systems research on online social networks. *Communcations of the Association for Information Systems*, *35(1)*(8), 145–172.

Blank, G., & Lutz, C. (2016). The social structuration of six major social media platforms in the United Kingdom: Facebook, LinkedIn, Twitter, Instagram, Google+ and Pinterest. In *Proceedings of the 7th 2016 International Conference on Social Media & Society* (p. 8). ACM.

Borgatti, SP., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science*, *323*(5916), 892–895.

Borgatti, S., & Foster, P. (2003). The network paradigm in organizational research: A review and typology. *Journal of Management*, *29*(6), 991–101.

Borgatti, S., & Halgin, D. (2011). On network theory. *Organization Science*, *22*(5), 1168–

1181.

Boudreau, M., Gefen, D., & Straub, D. (2001). Validation in information systems research: a state-of-the-art assessment. *MIS Quarterly*, *25*(1), 1–16.

Bourdieu, P. (1986). The forms of capital. In *Handbook of Theory and Research for the Sociology of Education* (pp. 241–258). Greenwood, New York.

Boyd, D. (2008). *Taken out of context: American teen sociality in networked publics*. University of California, Berkeley.

Boyd, D. (2010). Social Network Sites as Networked Publics: Affordances, Dynamics, and Implications. In Z. Papacharissi (Ed.), *Networked Self: Identity, Community, and Culture on Social Network Sites* (pp. 39–58). New York: Routledge.

Boyd, D., & Ellison, N. (2008). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication*, *13*(1), 210–230.

Brandtzæg, P., & Heim, J. (2009). Why people use social networking sites. In *In International Conference on Online Communities and Social Computing* (pp. 143–152). Springer Berlin Heidelberg.

Bregman, A., & Haythornthwaite, C. (2003). Radicals of presentation: visibility, relation, and co-presence in persistent conversation. *New Media & Society*, *5(1)*, 117–140.

Brooks, L., & Anene, V. (2012). Information disclosure and generational differences in social network sites. In *AMCIS 2012 Proceedings. Paper 10*.

Brown, J., Broderick, A., & Lee, N. (2007). Word of mouth communication within online communities: Conceptualizing the online social network. *Journal of Interactive Marketing*, *21*(3), 2–20.

Bucher, T., & Helmond, A. (2016). The affordances of social media platforms. In J. Burgess, T. Poell, & A. Marwick (Eds.), *The SAGE Handbook of Social Media*. SAGE Publications.

Bulut, Z. A., & Doğan, O. (2017). The ABCD typology: Profile and motivations of Turkish social network sites users. *Computers in Human Behavior*, *67*, 73–83.

Burke, M., & Kraut, R. (2014). Growing closer on Facebook: Changes in tie strength through social network site use. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 4187-4196. ACM.).

Burke, M., Kraut, R., & Marlow, C. (2011). Social capital on facebook: differentiating uses and users. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 571–580). New York, New York, USA: ACM Press.

Burke, M., Marlow, C., & Lento, T. (2010). Social network activity and social well-being. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 1909–1912). ACM.

Burt, R. (2012). *Structural Holes [1992]*. *Contemporary Sociological Theory*.

Caplan, S., Williams, D., & Yee, N. (2009). Problematic Internet use and psychosocial well-being among MMO players. *Computers in Human Behavior*, *25*(6), 1312–1319.

Chakraborty, R., Vishik, C., & Rao, H. (2013). Privacy preserving actions of older adults on social media: Exploring the behavior of opting out of information sharing. *Decision Support Systems*, *55(4)*, 948–956.

Chang, S. E., Liu, A. Y., & Shen, W. C. (2017). User trust in social networking services: A comparison of Facebook and LinkedIn. *Computers in Human Behavior*, *69*, 207–

217.

Chen, H., & Beaudoin, C. E. (2016). An empirical study of a social network site: Exploring the effects of social capital and information disclosure. *Telematics and Informatics*, *33*(2), 432–435. https://doi.org/10.1016/J.TELE.2015.09.001

Chen, R. (2013). Living a private life in public social networks: An exploration of member self-disclosure. *Decision Support Systems*, *55*(3), 661–668.

Chiang, J. K.-H., & Suen, H.-Y. (2015). Self-presentation and hiring recommendations in online communities: Lessons from LinkedIn. *Computers in Human Behavior*, *48*, 516–524.

Chin, W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, *295*(2), 295–336.

Chin, W. (2010). How to write up and report PLS analyses. In *Handbook of partial least squares (pp.655-690)*. Springer Berlin Heidelberg.

Cohen, J. (1992). A Power Primer. *Psychological Bulletin*, *112*(1), 155–159.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Routledge.

Coleman, J. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, *94*, S95–S120.

Cook, K., & Emerson, R. (1978). Power, equity and commitment in exchange networks. *American Sociological Review*, 721–739.

Cross, R., Parker, A., & Borgatti, S. (2002). A bird's-eye view: Using social network analysis to improve knowledge creation and sharing. *IBM Institute for Business Value*, 1669–1700.

Damaschke, K. (2012). *First impression 2.0: competency representation on LinkedIn.*

Dey, A. K., & de Guzman, E. (2006). From awareness to connectedness. In *Proceedings of the SIGCHI conference on Human Factors in computing systems - CHI '06* (p. 899). New York, New York, USA: ACM Press. https://doi.org/10.1145/1124772.1124905

Diamantopoulos, A., & Winklhofer, H. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, *38(2)*, 269–277.

Djonov, E., & Van Leeuwen, T. (2018). Social media as semiotic technology and social practice: the case of ResearchGate's design and its potential to transform social practice. *Social Semiotics*, *28*(5), 641–664.

Dominick, J. (1999). Who do you think you are? Personal home pages and self-presentation on the World Wide Web. *Journalism & Mass Communication Quarterly*, *76(4)*, 646–658.

Donath, J., & Boyd, D. (2004). Public displays of connection. *Bt Technology Journal*, *22(4)*, 71–82.

Ellison, N. , Lampe, C., Steinfield, C., & Vitak, J. (2011). With a little help from my friends: How social network sites affect social capital processes. In *The networked self: Identity, community and culture on social network sites (ed. Zizi Papacharissi)* (pp. 124–146).

Ellison, N. (2007). Facebook use on campus: A social capital perspective on social network sites. *ECAR Symposium, Boca Raton, FL*.

Ellison, N., & Boyd, D. (2013). Sociality through Social Network Sites. In *Dutton, W. H.*

*(Ed.), The Oxford Handbook of Internet Studies. Oxford* (pp. 151–172). Oxford University Press.

Ellison, N., Hancock, J., & Toma, C. (2012). Profile as promise: A framework for conceptualizing veracity in online dating self-presentations. *New Media & Society*, *14(1)*, 45–62.

Ellison, N., Steinfield, C., & Lampe, C. (2006). Spatially bounded online social networks and social capital. *International Communication Association, 36*, 1–37.

Ellison, N., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends:" Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication*, *12*(4), 1143–11168.

Ellison, N., Steinfield, C., & Lampe, C. (2011). Connection strategies: Social capital implications of Facebook-enabled communication practices. *New Media & Society*, *13*(6), 873–892. https://doi.org/1461444810385389

Ellison, N., & Vitak, J. (2015). Social network site affordances and their relationship to social capital processes. In S. Sundar (Ed.), *The handbook of psychology of communication technology* (pp. 205–227).

Ellison, N., Vitak, J., & Gray, R. (2014). Cultivating social resources on social network sites: Facebook relationship maintenance behaviors and their role in social capital processes. *Journal of Computer-Mediated Communication*, *19*(4), 855–870.

Ellison, N., Vitak, J., Gray, R., & Lampe, C. (2014). Cultivating social resources: The relationship between bridging social capital and Facebook use among adults. *Journal of Computer-Mediated Communication*, *19*(4), 855–870.

Evans, S. K., Pearce, K. E., Vitak, J., & Treem, J. W. (2017). Explicating Affordances: A Conceptual Framework for Understanding Affordances in Communication Research. *Journal of Computer-Mediated Communication*, *22*(1), 35–52.

Falk, R., & Miller, N. (1992). *A primer for soft modeling.* University of Akron Press.

Fornell, C., & Bookstein, F. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, 440–452.

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Forret, M., & Dougherty, T. (2001). Correlates of networking behavior for managerial and professional employees. *Group & Organization Management*, *26*(3), 288–311.

Gabarron, E., Årsand, E., & Wynn, R. (2018). Social Media Use in Interventions for Diabetes: Rapid Evidence-Based Review. *Journal of Medical Internet Research*, *20*(8), e10303. https://doi.org/10.2196/10303

Galloway, A., & Henry, M. (2014). Relationships between social connectedness and spirituality and depression and perceived health status of rural residents. *Online Journal of Rural Nursing and Health Care*, *14*(2), 43–79.

Garg, R., & Telang, R. (2012). Role of online social networks in job search by unemployed individuals. In *Thirty Third International Conference on Information Systems*. Orlando 2012.

Gefen, D., & Straub, D. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information Systems*, *16*(1), 91–109.

Gefen, D., Straub, D., & Boudreau, M. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, *4*(1), Article 7.

Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika*, *61*(1), 101–107.

Globalwebindex. (2018). *GWI Social Q2.2017*. Retrieved from http://insight.globalwebindex.net/social

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology*, *78(6)*, 1360–1380.

Granovetter, M. (1983). The strength of weak ties: A network theory revisited. *Sociological Theory*, *1(1)*, 201–233.

Grieve, R., Indian, M., Witteveen, K., Tolan, G. ., & Marrington, J. (2013). Face-to-face or Facebook: Can social connectedness be derived online? *Computers in Human Behavior*, *29*(3), 604–609.

Grieve, R., & Kemp, N. (2015). Individual differences predicting social connectedness derived from Facebook: Some unexpected findings. *Computers in Human Behavior*, *51*(1), 239-243.

Gross, R., & Acquisti, A. (2005). Information revelation and privacy in online social networks. *Proceedings of the 2005 ACM Workshop on Privacy*, (ACM), 71–80.

Haferkamp, N., Eimler, S. C., Papadakis, A.-M., & Kruck, J. V. (2012). Men Are from Mars, Women Are from Venus? Examining Gender Differences in Self-Presentation on Social Networking Sites. *Cyberpsychology, Behavior, and Social Networking*, *15*(2), 91–98. https://doi.org/10.1089/cyber.2011.0151

Hagg, E., Dahinten, V. S., & Currie, L. M. (2018). The emerging use of social media for health-related purposes in low and middle-income countries: A scoping review. *International Journal of Medical Informatics*, *115*, 92–105.

Hair, J. . F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433.

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152.

Hampton, K., & Wellman, B. (2003). Neighboring in Netville: How the Internet supports community and social capital in a wired suburb. *City & Community*, *2*(4), 277–311.

Heidemann, J., Klier, M., & Probst, F. (2012). Online social networks: A survey of a global phenomenon. *Computer Networks*, *56*(18), 3866–3878.

Hemsley, J., & Mason, R. (2013). Knowledge and knowledge management in the social media age. *Journal of Organizational Computing and Electronic Commerce*, *23(1-2)*.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *New challenges to international marketing* (pp. 277–319). Emerald Group Publishing Limited.

Huang, C. (2019). Social network site use and Big Five personality traits: A meta-analysis. *Computers in Human Behavior, 97*, 280–290.

Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer, 30(2),* 199–218.

Jose, P. E., Ryan, N., & Pryor, J. (2012). Does Social Connectedness Promote a Greater Sense of Well-Being in Adolescence Over Time? *Journal of Research on Adolescence*, *22*(2), 235–251. https://doi.org/10.1111/j.1532-7795.2012.00783.x

Kane, G. C., Alavi, M., Labianca, J., & Borgatti, S. (2014). Integrating Social Networks and Information Systems: A review and framework for research. *MIS Quarterly*, *38(1)*, 275–304.

Kane, G., Alavi, M., & Labianca, G. (2014). What's different about social media networks? A framework and research agenda. *MIS Quarterly*, *38(1),* 275–304.

Kaplan, A. A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53*(1), 59–68.

Karahanna, E., Xu, S., Xu, Y., & Zhang, N. . (2018). The Needs–Affordances–Features Perspective for the Use of Social Media. *Management Information Systems Quarterly*, *42*(3), 737–756.

Kawachi, I., Subramanian, S., & Kim, D. (2008). Social capital and health. In *Social capital and health* (pp. 1–26). Springer New York.

Kempe, D., Kleinberg, J., & Tardos, É. (2003). Maximizing the spread of influence through a social network. In *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 137-146). ACM.*

Khan, M. L. (2017). Social media engagement: What motivates user participation and consumption on YouTube? *Computers in Human Behavior*, *66*, 236–247. https://doi.org/10.1016/J.CHB.2016.09.024

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons*, *54*(3), 241–251.

Kim, J. W., & Chock, T. M. (2017). Personality traits and psychological motivations predicting selfie posting behaviors on social networking sites. *Telematics and Informatics*, *34*(5), 560–571. https://doi.org/10.1016/J.TELE.2016.11.006

Köbler, F., Riedl, C., Vetter, C., Leimeister, J., & Krcmar, H. (2010). *Social connectedness on Facebook: An explorative study on status message usage*. *Americas Conference on Information Systems (AMCIS).*

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration (IJeC)*, *11*(4), 1–10.

Koohikamali, M., Peak, D. A., & Prybutok, V. R. (2017). Beyond self-disclosure: Disclosure of information about others in social network sites. *Computers in Human Behavior, 69*, 29–42. https://doi.org/10.1016/J.CHB.2016.12.012

Korda, H., & Itani, Z. (2013). Harnessing Social Media for Health Promotion and Behavior Change. *Health Promotion Practice*, *14(1)*, 15–23.

Koroleva, K., Krasnova, H., Veltri, N., & Günther, O. (2011). It's all about networking! empirical investigation of social capital formation on social network sites. In *Proceedings of the International Conference on Information Systems*.

Krasnova, H., Hildebrand, T., Günther, O., & Kovrigin, A. (2008). Why Participate in an Online Social Network? An Empirical Analysis. In *ECIS 2008 Proceedings. Paper 33*.

Krasnova, H., Koroleva, K., & Veltri, N. (2010). Investigation of the network construction behavior on social networking sites. In *International Conference on Information Systems (ICIS)*.

Krasnova, H., Veltri, N., & Günther, O. (2012). Self-disclosure and privacy calculus on social networking sites: The role of culture. *Business & Information Systems Engineering*, *4(3)*, 127–135.

Lampe, C. (2015). Social Media and Social Capital. *The International Encyclopedia of Digital Communication and Society*, *10(1)*, 1–10.

Lampe, C., Ellison, N., & Steinfield, C. (2007). A familiar face (book): profile elements as signals in an online social network. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 435–444). ACM.

Laroche, M., Habibi, M., & Richard, M. (2013). To be or not to be in social media: How brand loyalty is affected by social media? *International Journal of Information Management*, *33(1)*, 76–82.

Ledbetter, A. M., Mazer, J. P., DeGroot, J. M., Meyer, K. R., Mao, Y., & Swafford, B. (2011). Attitudes toward online social connection and self-disclosure as predictors of

Facebook communication and relational closeness. *Communication Research*, *38*(1), 27–53.

Lee, R., Draper, M., & Lee, S. (2001). Social connectedness, dysfunctional interpersonal behaviors, and psychological distress: Testing a mediator model. *Journal of Counseling Psychology*, *48*(3), 310–318.

Lin, N. (1981). Social resources and instrumental action. In *Social Structure and Network Analysis, edited by Peter V . Marsden and Nan Lin . Beverly Hills, CA : Sage .* (pp. 131–145).

Lin, N. (1992a). Social Resource Theory. *Encyclopedia of Sociology*, *4*, 1936–1942.

Lin, N. (1992b). Social Resources Theory. In *Encyclopedia of Sociology, Volume 4, edited by Edgar F . Borgatta and Marie L . Borgatta. NY: Macmillan.* (pp. 1936–1942).

Lin, N. (1999a). Building a network theory of social capital. *Connections*, *22*(1), 28–51.

Lin, N. (1999b). Social networks and status attainment. *Annual Review of Sociology*, *25*(1), 467–487.

Lin, N. (2002a). *Social capital: A theory of social structure and action*. Cambridge university press.

Lin, N. (2002b). *Social capital: A theory of social structure and action (Vol.19)*. Cambridge university press.

Lin, N. (2008). A network theory of social capital. In *The handbook of social capital* (pp. 50–69).

Lin, N., Cook, K. S., & Burt, R. S. (2001). *Social capital : theory and research*. Aldine de Gruyter.

LinkedIn.com. (2019). LinkedIn.About Us. Retrieved April 9, 2019, from https://news.linkedin.com/about-us#statistics

LinkedIn Corporate Communications Team. (2019). LinkedIn releases new gender insights report. Retrieved May 12, 2019, from https://news.linkedin.com/2019/January/linkedin-releases-2019-gender-insights-report

Linn, H., Tov, W., & Qiu, L. (2014). Emotional disclosure on social networking sites: The role of network structure and psychological needs. *Computers in Human Behavior*, *41*, 342–350. https://doi.org/10.1016/J.CHB.2014.09.045

Linn, J.-H. T. (2019). Strategic Social Grooming: Emergent Social Grooming Styles on Facebook, Social Capital and Well-Being. *Journal of Computer-Mediated Communication*, 1–18. https://doi.org/10.1093/jcmc/zmz002

Linn, R., & Utz, S. (2017). Self-disclosure on SNS: Do disclosure intimacy and narrativity influence interpersonal closeness and social attraction? *Computers in Human Behavior, 70*, 426–436. https://doi.org/10.1016/j.chb.2017.01.012

Liu, J. S., Ho, M. H.-C., & Lu, L. Y. Y. (2017). Recent Themes in Social Networking Service Research. *PLOS ONE*, *12*(1), e0170293.

Lu, W., & Hampton, K. N. (2017). Beyond the power of networks: Differentiating network structure from social media affordances for perceived social support. *New Media & Society*, *19*(6), 861–879. https://doi.org/10.1177/1461444815621514

Mäntymäki, M., & Islam, A. K. M. N. (2016). The Janus face of Facebook: Positive and negative sides of social networking site use. *Computers in Human Behavior*, *61*, 14–

26. https://doi.org/10.1016/J.CHB.2016.02.078

Marwick, A., & Boyd, D. (2011). I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media & Society, 13*(1), 114–133.

McIntyre, E., Wiener, K., & Saliba, A. (2015). Compulsive Internet use and relations between social connectedness, and introversion. *Computers in Human Behavior*, *48*, 569–574.

Mehdizadeh, S. (2010). Self-presentation 2.0: Narcissism and self-esteem on Facebook. *Cyberpsychology, Behavior, and Social*, *13(4)*, 357–364.

Meng, J., Martinez, L., & Holmstrom, A. (2017). Research on social networking sites and social support from 2004 to 2015. *Cyberpsychology, Behavior, and Social Networking*, *20*(1), 44–51.

Meyers, L., Gamst, G., & Guarino, A. (2016). *Applied multivariate research: Design and interpretation*. Sage Publications.

Munzel, A., Galan, J. p., & Meyer-Waarden, L. (2018). Getting By or Getting Ahead on Social Networking Sites? The Role of Social Capital in Happiness and Well-Being. *International Journal of Electronic Commerce*, *22*(2), 232–257.

Myers, M. (2013). *Qualitative research in business and management*. Sage.

Nadkarni, A., & Hofmann, S. (2012). Why do people use Facebook? *Personality and Individual Differences*, *52*(3), 243–249.

Nardi, P. (2018). *Doing survey research: A guide to quantitative methods* (4th Editio). New York: Routledge.

Nie, N. (2001). Sociability, interpersonal relations, and the Internet: Reconciling conflicting findings. *American Behavioral Scientist*, *45*(3), 420–435.

Nie, & Sundar, S. (2013). Who would pay for Facebook? Self esteem as a predictor of user behavior, identity construction and valuation of virtual possessions. In *IFIP Conference on Human-Computer Interaction* (pp. 726–743). Springer Berlin Heidelberg.

Nolan, S., Hendricks, J., Williamson, M., & Ferguson, S. (2018). Social networking sites (SNS) as a tool for midwives to enhance social capital for adolescent mothers. *Midwifery*, *62*, 119–127.

Nunnally, J. C., & Bernstein, I. H. (1994). Validity. *Psychometric Theory*, *3*, 99–132.

Ortiz, J., Chih, W.-H., & Tsai, F.-S. (2018). Information privacy, consumer alienation, and lurking behavior in social networking sites. *Computers in Human Behavior*, *80*, 143–157. https://doi.org/10.1016/J.CHB.2017.11.005

Osman, M. (2019). Mind-Blowing LinkedIn Statistics and Facts (2019). Retrieved May 13, 2019, from https://kinsta.com/blog/linkedin-statistics/

Papacharissi, Z. (2009). The virtual geographies of social networks: a comparative analysis of Facebook, LinkedIn and ASmallWorld. *New Media & Society*, *11*(1–2), 199–220.

*Pew Research Center*. (2018).

Phua, J., Jin, S. V., & Kim, J. (Jay). (2017). Uses and gratifications of social networking sites for bridging and bonding social capital: A comparison of Facebook, Twitter, Instagram, and Snapchat. *Computers in Human Behavior*, *72*, 115–122. https://doi.org/10.1016/j.chb.2017.02.041

Pinsonneault, A., & Kraemer, K. (1993). Survey Research Methodology in Management

Information Systems: An Assessment. *Journal of Management Information Systems*, *10*(2), 75–105. https://doi.org/10.1080/07421222.1993.11518001

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879.

Praveena, K., & Thomas, S. (2018). Explaining user acceptance and usage of social networking sites: the role of trust, social connectedness and visibility in extending UTAUT2. *International Journal of Management Practice*, *11*(3), 318. https://doi.org/10.1504/IJMP.2018.092855

Putnam, R. (2000). *Bowling alone: The collapse and revival of American community*. Simon and Schuster.

Quinio, B., & Marciniak, R. (2013). Virtual Social Network characterization: reference framework for a comparative analysis. In *Thirty Fourth International Conference on Information Systems*. Milan, Italy.

Resnick, P. (2001). Beyond bowling together: Sociotechnical capital. *HCI in the New Millennium*, *77*, 247–272.

Richter, D., Riemer, K., Brocke, J., & Grobe, B. (2009). Internet social networking-distinguishing the phenomenon from its manifestations in web sites. In *ECIS 2009 Proceedings* (p. 331).

Riedl, C., Köbler, F., Goswami, S., & Krcmar, H. (2013). Tweeting to Feel Connected: A Model for Social Connectedness in Online Social Networks. *International Journal of Human-Computer Interaction*, *29*(10), 670–687.

Roldán, J., & Sánchez-Franco, M. (2012). *Variance-based structural equation modeling: guidelines for using partial least squares*. *Research methodologies, innovations and philosophies in software systems engineering and information systems*. IGI Global.

Rossiter, J. (2002). The C-OAR-SE procedure for scale development in marketing. *International Journal of Research in Marketing, 19(4),* 305–335.

Safko, L., & Brake, D. (2009). The Social Media Bible–Tactics. *Tools & for Business Success, Hoboken, New Jersey*.

Salancik, G., & Burt, R. (1995). Wanted: A good network theory of organization. *Admin. Sci. Quart*, *40(2)*, 345–349.

Schaefer, C. (2008). Motivations and Usage Patterns on Social Network Sites. In *ECIS 2008 Proceedings* (pp. 2088–2099).

Schneider, F., Feldmann, A., Krishnamurthy, B., & Willinger, W. (2009). Understanding online social network usage from a network perspective. In *Proceedings of the 9th ACM SIGCOMM conference on Internet measurement* (pp. 35–48). ACM.

Seabrook, E., Kern, M., & Rickard, N. (2016). Social networking sites, depression, and anxiety: a systematic review. *JMIR Mental Health*, *3*(4), e50.

See-To, E., & Ho, K. (2014). Value co-creation and purchase intention in social network sites: The role of electronic Word-of-Mouth and trust–A theoretical analysis. *Computers in Human Behavior*, *31*, 182–189.

Seidman, G. (2013). Self-presentation and belonging on Facebook: How personality influences social media use and motivations. *Personality and Individual Differences*, *54(3)*, 402–407.

Shen, C., & Gong, H. (2019). Personal ties, group ties and latent ties: connecting network size to diversity and trust in the mobile social network WeChat. *Asian Journal of Communication*, *29*(1), 18–34. https://doi.org/10.1080/01292986.2018.1504976

Shi, J., Poorisat, T., & Salmon, C. T. (2018). The Use of Social Networking Sites (SNSs) in Health Communication Campaigns: Review and Recommendations. *Health Communication*, *33*(1), 49–56. https://doi.org/10.1080/10410236.2016.1242035

Short, J., Williams, E., & Christie, B. (1976). *The social psychology of telecommunications*. John Wiley & Sons.

Sinclair, T. J., & Grieve, R. (2017). Facebook as a source of social connectedness in older adults. *Computers in Human Behavior*, *66*(1), 363–369.

Siraj, A. (2018). Impact of Internet Use on Social Capital: Testing Putnam's Theory of Time Displacement in Urban Pakistan. *The Journal of Social Media in Society*, *7*(1).

Skues, J., Williams, B., & Wise, L. (2012). The effects of personality traits, self-esteem, loneliness, and narcissism on Facebook use among university students. *Computers in Human Behavior*, *28(6)*, 2414–2419.

Smith, E. J., Marcum, C. S., Boessen, A., Almquist, Z. W., Hipp, J. R., Nagle, N. N., & Butts, C. T. (2015). The relationship of age to personal network size, relational multiplexity, and proximity to alters in the Western United States. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *70*(1), 91–99. https://doi.org/10.1093/geronb/gbu142

Smith, R. (2018). *The Effects of Generation Y's Investment in Multiple Social Network Sites on Social Connectedness and Wellbeing*.

Son, J.-E., Lee, S.-H., Cho, E.-Y., & Kim, H.-W. (2016). Examining online citizenship behaviours in social network sites: a social capital perspective. *Behaviour & Information Technology*, *35*(9), 730–747. https://doi.org/10.1080/0144929X.2016.1143032

Spies Shapiro, L. A., & Margolin, G. (2014). Growing Up Wired: Social Networking Sites and Adolescent Psychosocial Development. *Clinical Child and Family Psychology Review*, *17*(1), 1–18. https://doi.org/10.1007/s10567-013-0135-1

Statista.com. (2017). • Global daily social media usage 2015 | Statistic. Retrieved from http://www.statista.com/statistics/433871/daily-social-media-usage-worldwide/

Statista.com. (2018). LinkedIn: number of users | Statistic. Retrieved from http://www.statista.com/statistics/274050/quarterly-numbers-of-linkedin-members/

Steinfield, C., Ellison, N., & Lampe, C. (2008). Social capital, self-esteem, and use of online social network sites: A longitudinal analysis. *Journal of Applied Developmental Psychology*, *29(6)*, 434–445.

Steinfield, C., Ellison, N., Lampe, C., & J, V. (2013). Online social network sites and the concept of social capital. In *Frontiers in new media* (Vol. 15, pp. 115–131). Routledge.

Stone, M. (1974). Cross-Validatory Choice and Assessment of Statistical Predictions. *Journal of the Royal Statistical Society: Series B (Methodological)*, *36*(2), 111–133. https://doi.org/10.1111/j.2517-6161.1974.tb00994.x

Stone, S., & Logan, A. (2018). Exploring Students' Use of the Social Networking Site WhatsApp to foster connectedness in the online learning experience. *Irish Journal of Technology Enhanced Learning Ireland*, *3*(1), 42–55.

Straub, D., Boudreau, M., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information Systems*, *13*(1), 24.

Sturgis, P., Patulny, R., Allum, N., & Buscha, F. (2012). Social connectedness and generalized trust: a longitudinal perspective. In *Handbook of Research Method and Applications in Social Capital (ed. Yaojun Lee )* (pp. 76–91).

Stutzman, F., Capra, R., & Thompson, J. (2011). Factors mediating disclosure in social network sites. *Computers in Human Behavior, 27(1)*, 590–598.

Tang, G., & Lee, F. L. F. (2013). Facebook Use and Political Participation. *Social Science Computer Review*, *31*(6), 763–773. https://doi.org/10.1177/0894439313490625

Tian, X. (2016). Network domains in social networking sites: expectations, meanings, and social capital. *Information, Communication & Society*, *19*(2), 188–202. https://doi.org/10.1080/1369118X.2015.1050051

Tiwari, S., Lane, M., & Alam, K. (2019). Do social networking sites build and maintain social capital online in rural communities? *Journal of Rural Studies*, *66*, 1–10. https://doi.org/10.1016/J.JRURSTUD.2019.01.029

Treem, J., & Leonardi, P. (2013). Social media use in organizations: Exploring the affordances of visibility, editability, persistence, and association. *Annals of the International Communication Association*, *36(1)*, 143–189.

Trepte, S., & Behavior, L. R. (2013). The reciprocal effects of social network site use and the disposition for self-disclosure: A longitudinal study. *Computers in Human Behavior*, *29*(3), 1102–1112.

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

Tsay-Vogel, M., Shanahan, J., & Signorielli, N. (2018). Social media cultivating perceptions of privacy: A 5-year analysis of privacy attitudes and self-disclosure behaviors among Facebook users. *New Media & Society*, *20*(1), 141–161. https://doi.org/10.1177/1461444816660731

Tufekci, Z. (2008). Can you see me now? Audience and disclosure regulation in online social network sites. *Bulletin of Science, Technology & Society*, *28*(1), 20–36.

Utz, S. (2015a). Is LinkedIn making you more successful? The informational benefits derived from public social media. *New Media & Society*, *18(11)*, 2685–2702.

Utz, S. (2015b). The function of self-disclosure on social network sites: Not only intimate, but also positive and entertaining self-disclosures increase the feeling of connection. *Computers in Human Behavior*, *45*, 1–10.

Utz, S., & Breuer, J. (2016). Informational benefits from social media use for professional purposes: Results from a longitudinal study. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, *10*(4), article 3.

Utz, S., & Breuer, J. (2019). The Relationship Between Networking, LinkedIn Use, and Retrieving Informational Benefits. *Cyberpsychology, Behavior, and Social Networking*, *22*(3), 180–185. https://doi.org/10.1089/cyber.2018.0294

Valenzuela, M., & Sachdev, P. (2009). Can cognitive exercise prevent the onset of dementia? Systematic review of randomized clinical trials with longitudinal follow-up. *The American Journal of Geriatric Psychiatry*. Retrieved from http://www.sciencedirect.com/science/article/pii/S106474811261598X

Valenzuela, S., Park, N., & Kee, K. (2009). Is there social capital in a social network site?: Facebook use and college students' life satisfaction, trust, and participation1. *Journal of Computer-Mediated*, *14(4)*, 875–901.

Vehovar, V., Lozar Manfreda, K., Koren, G., & Hlebec, V. (2008). Measuring ego-centered social networks on the web: Questionnaire design issues. *Social Networks*, *30*(3), 213–222. Retrieved from https://www.sciencedirect.com/science/article/pii/S0378873308000142

Venkatesh, V., Brown, S., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, *37(1)*, 21–54.

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do Social Network Sites Enhance or Undermine Subjective Well-Being? A Critical Review. *Social Issues and Policy Review*, *11*(1), 274–302. https://doi.org/10.1111/sipr.12033

Vitak, J. (2012). *Keeping connected in the Facebook age: The relationship between Facebook use, relationship maintenance strategies, and relational outcomes*. Michigan State University. Communication Arts and Sciences {u2013} Media and Information Studies.

Vitak, J., & Ellison, N. (2013). "There'sa network out there you might as well tap": Exploring the benefits of and barriers to exchanging informational and support-based resources on Facebook. *New Media & Society*, *15(2)*, 243–259.

Wang, J.-L., Gaskin, J., Rost, D. H., & Gentile, D. A. (2018). The Reciprocal Relationship Between Passive Social Networking Site (SNS) Usage and Users' Subjective Well-

Being. *Social Science Computer Review*, *36*(5), 511–522. https://doi.org/10.1177/0894439317721981

Webster, J., & Trevino, L. K. (1995). Rational and Social Theories as Complementary Explanations of Communication Media Choices: Two Policy-Capturing Studies. *Academy of Management Journal*, *38*(6), 1544–1572. https://doi.org/10.5465/256843

Wehner, B., Ritter, C., & Leist, S. (2017). Enterprise social networks: A literature review and research agenda. *Computer Networks*, *114*, 125–142. https://doi.org/10.1016/J.COMNET.2016.09.001

Weiss, R. (1974). The provisions of social relationships. In *Z. Rubin (ed.), Doing Unto Others. Englewood Cliffs, NJ, Prentice-Hall, 1974, pp. 17-26.*

Whiting, A., & Williams, D. (2013). Why people use social media: a uses and gratifications approach. *Qualitative Market Research: An International Journal*, *16*(4), 362–369.

Wu, Y.-J., Outley, C., Matarrita-Cascante, D., & Murphrey, T. P. (2016). A Systematic Review of Recent Research on Adolescent Social Connectedness and Mental Health with Internet Technology Use. *Adolescent Research Review*, *1*(2), 153–162. https://doi.org/10.1007/s40894-015-0013-9

Yin, G., Cheng, X., & Zhu, L. (2011). Understanding continuance usage of social networking services: A theoretical model and empirical study of the chinese context. In *Thirty Second International Conference on Information Systems*. Shanghai.

Yu, R. P. (2016). The relationship between passive and active non-political social media use and political expression on Facebook and Twitter. *Computers in Human Behavior*, *58*, 413–420. https://doi.org/10.1016/J.CHB.2016.01.019

Yuan, C., & Fussell, S. (2017). A tale of two sites: Dual social network site use and social network development. *Computers in Human Behavior*, *74*, 83–91.

Zagaar, U., & Paul, S. (2012). Knowledge sharing in online cancer survivorship community system: A theoretical framework. In *AMCIS 2012 Proceedings. Paper 20.*

Zhang, Y., & Leung, L. (2015). A review of social networking service (SNS) research in communication journals from 2006 to 2011. *New Media & Society*, *17*(7), 1007–1024.

Zide, J., Elman, B., & Shahani-Denning, C. (2014). LinkedIn and recruitment: How profiles differ across occupations. *Employee Relations, 36*(5), 583–604.

Zúñiga, Homero, G. de, Jung, N., & Valenzuela, S. (2012). Social Media Use for News and Individuals' Social Capital, Civic Engagement and Political Participation. *Journal of Computer-Mediated Communication*, *17*(3), 319–336. https://doi.org/10.1111/j.1083-6101.2012.01574.x

Zúñiga, H. G. de, Barnidge, M., & Scherman, A. (2017). Social Media Social Capital, Offline Social Capital, and Citizenship: Exploring Asymmetrical Social Capital Effects. *Political Communication*, *34*(1), 44–68. https://doi.org/10.1080/10584609.2016.1227000

# Appendix 1: Online Consent Preamble

**1. The "Preamble" Statement:**

This survey is administered by:

**Student Investigator:**
Morteza Mashayekhi
DeGroote School of Business
McMaster University
E-mail: mashaym@mcmaster.ca

**Faculty Supervisor:**
Dr. Milena Head
DeGroote School of Business
McMaster University
E-mail: Headm@mcmaster.ca

The purpose of the survey is to propose an integrated model that explains the process by which individuals develop and accrue social capital through using SNS such as LinkedIn. In this research social capital is defined as "Investment (through action) in social relations by individuals through which they gain access to embedded resources in a social structure and reap the benefits of valued resources" (Lin, 2008). Information gathered during this survey will be written up as a thesis. What we learn from this survey will help us understand how people can increase their social capital through the use of professionally-oriented social network sites.

To learn more about the survey and the researcher's study, particularly in terms of any associated risks or harms associated with the survey, how confidentiality and anonymity will be handled, withdrawal procedures, incentives that are promised, how to obtain information about the survey's results, how to find helpful resources should the survey make you uncomfortable or upset etc., please read the accompanying letter of information.

This survey should take approximately 30 minutes to complete. People filling out this survey must actively use LinkedIn. Participants will be compensated the amount they agreed upon before they entered into the survey.

This survey is part of a study that has been reviewed and cleared by the McMaster Research Ethics Board (MREB). The MREB protocol number associated with this survey is 2017-192

You are free to complete this survey or not. If you have any concerns or questions about your rights as a participant or about the way the study is being conducted, please contact:

McMaster Research Ethics Secretariat
Telephone 1-(905) 525-9140 ext. 23142
C/o Research Office for Administration, Development and Support (ROADS)
E-mail: ethicsoffice@mcmaster.ca

**The “Consent to Participate” Statement:**

Having read the above, I understand that by clicking the “Yes” button below, I agree to take part in this study under the terms and conditions outlined in the accompanied letter of information.

"I agree to participate."
"I do not agree to participate."

**3. The “Do Not Agree to Participate” Statement:**

Thank you. You have decided not to participate in this survey. No data has been collected from you.

**4. The “Quit” Statement:**

Thank you. You have decided to quit this survey. None of your survey responses have been collected or stored.

**5. The “Thank You for Completing the Survey” statement:**

Thank you for taking this survey. Your answers are a valuable part of this research

## Appendix 2: Online Survey Questions

To answer to questions 1-15 please first login to your LinkedIn account and follow the following steps:

- Click the Me icon at top of your LinkedIn homepage.
- Click View profile.
- On the right rail of the page, click the Edit icon next to Contact and Personal Info.
- Briefly review your information in "Edit intro" pop-up window.

Q1- Do you have a profile photo?
- o Yes
- o No

Q2- Have you used in your Headline most or all of the 120 available characters and included your most important keywords?
- o Yes
- o No

Q3- In case you are looking for a job, have you mentioned in your Headline that you are seeking for a job in your field of interest?
- o Yes
- o No
- o NA (I am not looking for a job at the current time)

Q4- How clearly does your profile Summary explain what you've accomplished, what you currently do, and the types of people you would like to meet and connect with?
- o I have no Summary
- o Somewhat (1 short paragraph, mostly historical info)
- o Pretty good (1-3 short paragraphs, current business highlighted)
- o Excellent (close to 2,000 characters, keywords, clear explanation of what I've accomplished, what I do, and who I would like to meet)

Q5- Have you added or linked your profile to external documents, photos, sites, videos or presentations?
- o Yes
- o No

Q6- Have you included your preferred contact information on your profile?
- o Yes
- o No

Q7- Have you included recommendation(s) from previous or current colleagues on your profile?

- Yes
- No

Q8- How many skills you have reported on your profile?

- No Skills reported
- 1-10
- 11-20
- 21-30
- 31-40
- 41-50

Q9- Have you included volunteer activities on your profile?

- Yes
- No

Q10- Have you mentioned your current position in your profile?

- Yes
- No

Q11- Have you mentioned your education level in your profile?

- Yes
- No

Q12- Have you specified your industry you are working now in your profile?

- Yes
- No

Q13- Have you mentioned your current location in your profile?

- Yes
- No

Q14- How many 1st level connections do you currently have on LinkedIn?

- 0-50
- 51-100
- 101-150
- 151-200
- 201-250
- 251-300
- 301-400
- 401-500
- 500+ (9)

Q15- How many LinkedIn groups are you a member of?

- 0
- 1-10
- 11-20
- 21-30
- 31-50

Q16- Please indicate the extent to which you agree with the following statements: from Strongly agree (1) to Strongly disagree (7)

- I have a comprehensive profile on LinkedIn.
- I have a detailed profile on LinkedIn.
- My profile tells a lot about me.
- From my LinkedIn profile it would be easy to find out my skills and competencies.

Q17- Please indicate the extent to which (on average) you perform the following actions on LinkedIn based on the following scale: Almost Never (1), A Few Times in a Year (2) ,Almost Monthly (3) Every 2-3 Weeks (4), Almost Weekly (5), Every 2-3 Days (6), Almost Everyday (7):

- Commenting on posts
- Share something on your wall
- Like what connections post.
- Follow the news of your connections.
- Look through the News-feed.
- Click on the content shared by connections.

Q18- Please indicate the extent to which you agree with the following statements: from Strongly agree (1) to Strongly disagree (7)

On LinkedIn, I

- Feel close to the people in my connection list.
- Have a feeling of being connected to others.
- Updated about my connections.
- Stay in touch with my connections.

- Keep contact with the people in my connection list.
- Interact with my connections more

Q19- Please indicate the extent to which you agree with the following statements: from Strongly agree (1) to Strongly disagree (7)

- I receive information about job opportunities from my LinkedIn connections/groups
- I get information about job market from my LinkedIn connections/groups
- Through my network connections on LinkedIn I can get easily valuable referrals.
- My LinkedIn connections elevate my social credentials in my field of work.
- Some of my LinkedIn connections/groups boost my identity and recognition.
- Information shared by my LinkedIn connections/groups is sufficiently timely.

Q20 What is your age? Please choose only one of the following:

- 18-24 (1)
- 25-34 (2)
- 35-44 (3)
- 45-54 (4)
- 55-64 (5)
- 65+ (6)
- Prefer Not To Say/Not Applicable (7)

Q21 What is your gender? Please choose only one of the following:

- Female (1)
- Male (2)
- Other (3)
- Prefer Not To Say/Not Applicable (4)

Q22 What is your highest level of education obtained? Please choose only one of the following:

- o High school diploma (1)
- o College diploma (2)
- o University – Undergraduate Bachelor's Degree (3)
- o University – Master's Degree (4)
- o University – Doctoral Degree (5)
- o Prefer Not To Say/Not Applicable (6)

Q23 What is your current employment status? Please choose only one of the following:

- o Employed (Full time or part time) (1)
- o Out of work (2)
- o Homemaker (3)
- o Student (4)
- o Retired (5)
- o Prefer Not To Say/Not Applicable (6)

Q24 If a student, what type of diploma / degree are you working towards? Please choose only one of the following:

- o High school diploma (1)
- o College diploma (2)
- o University – Undergraduate Bachelor's Degree (3)
- o University – Master's Degree (4)
- o University – Doctoral Degree (5)
- o Prefer Not To Say/Not Applicable (6)

Q25 How long have you been a member of LinkedIn? Please choose only one of the following:

- o Less than 6 months (1)
- o Months to year (2)
- o 1-2 years (3)
- o More than 2 years (4)

Q26 Are you actively looking for a job?

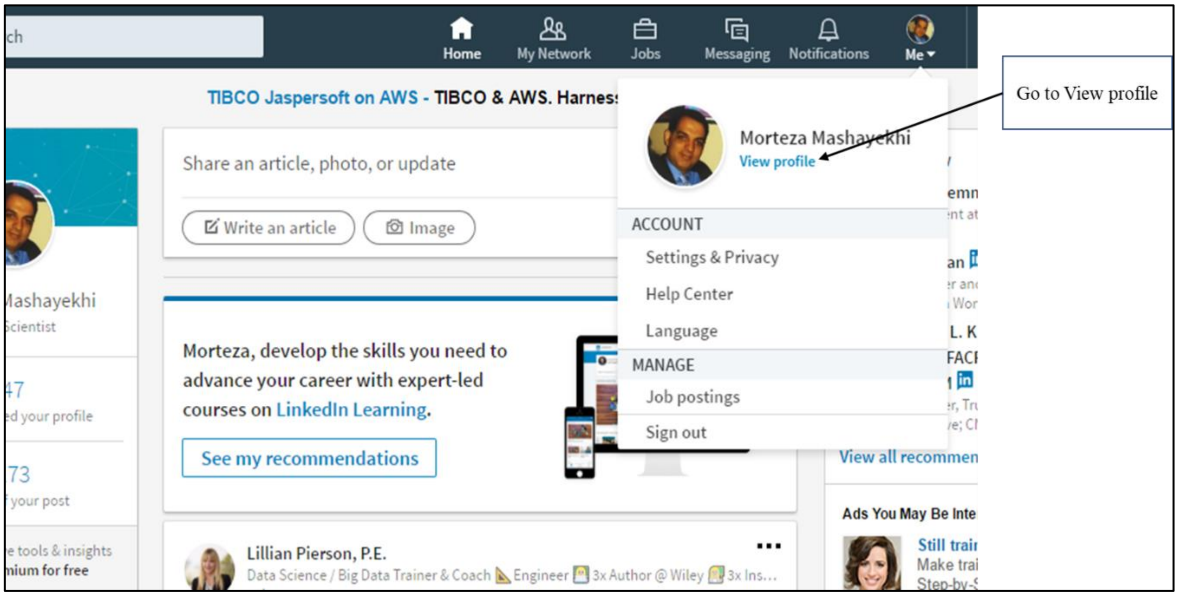
- Yes (1)
- No (2)

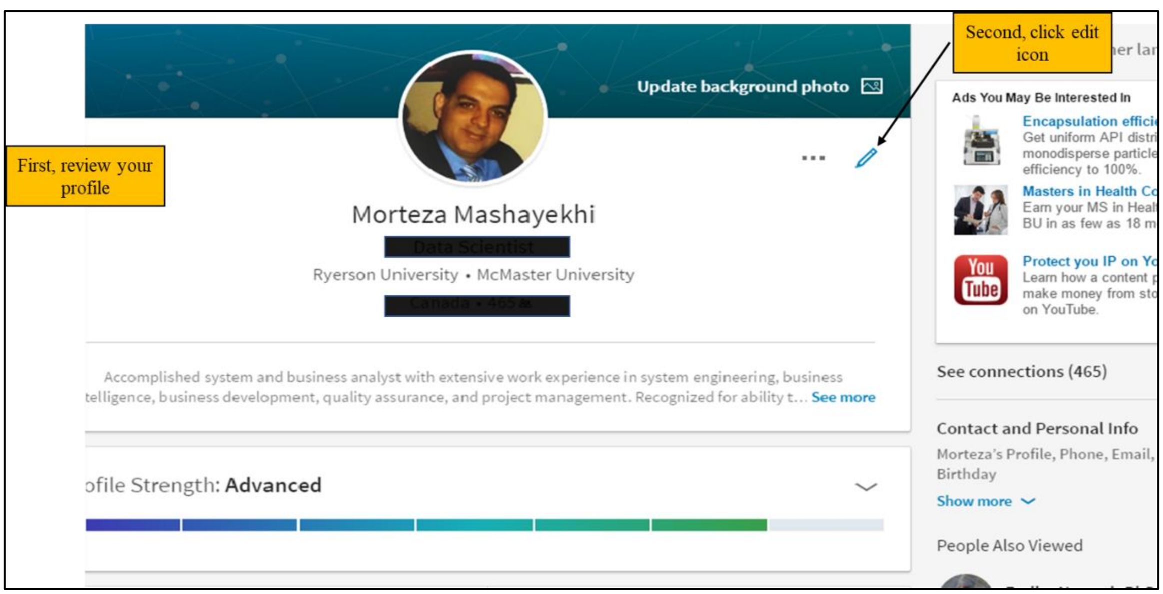
Q27 Are you an emigrant to Canada?

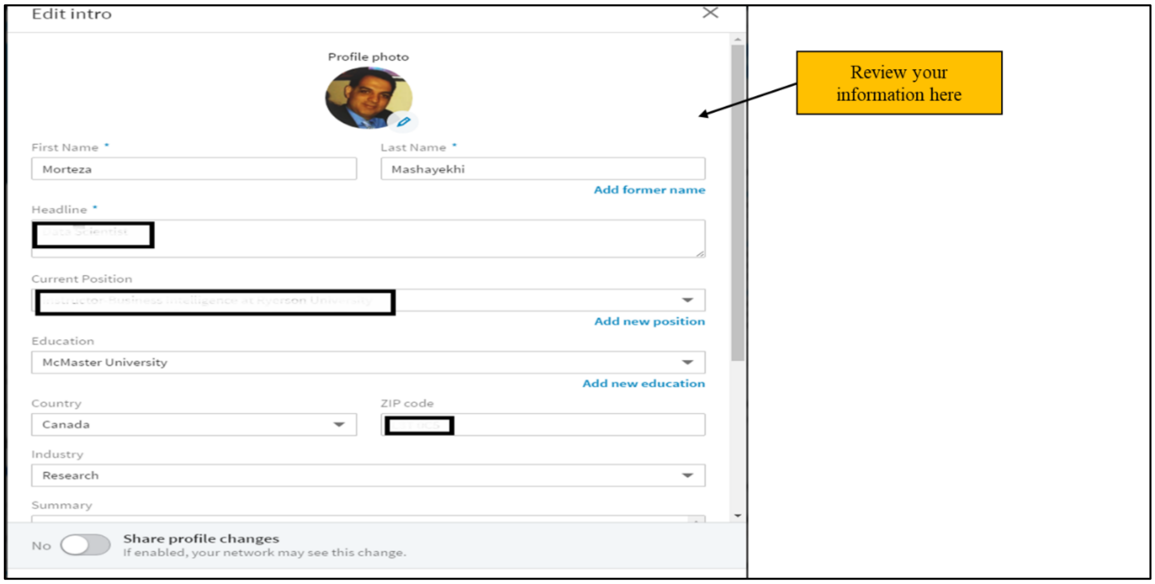
- Yes (1)
- No (I was born in Canada) (2)
- Not Applicable (3)

Q28- Please indicate why you mainly use LinkedIn. In addition, if you have any comments about how useful LinkedIn is for your networking efforts, please mention.

# Appendix 3: Tutorial Pictures Used in the Online Survey




Edit intro
Profile photo
First Name *
Morteza
Last Name *
Mashayekhi
Add former name
Headline *
Current Position
Add new position
Education
McMaster University
Add new education
Country
Canada
ZIP code
Industry
Research
Summary
No
Share profile changes
If enabled, your network may see this change.
Review your information here

# Appendix 4: Source and Adapted Research Scales

| Perceived Profile Disclosure | |
|---|---|
| **Source** | **Adapted** |
| **Krasnova and Veltri's (2010)**<br>• I have a comprehensive profile on FB.<br>• I always find time to keep my profile up-to-date.<br>• I have a detailed profile on FB.<br>• My profile tells a lot about me.<br>• From my FB profile it would be easy to find out my preferences in music, movies or books.<br>• From my FB profile it would be easy to understand what person I am. | • I have a comprehensive profile on LinkedIn.<br>• I have a detailed profile on LinkedIn.<br>• My profile tells a lot about me.<br>• From my LinkedIn profile it would be easy to find out my skills and competencies. |

| Active Participation | |
|---|---|
| **Source** | **Adapted** |
| **Koroleva et al., 2011**<br>• Post something<br>• Share thoughts and feelings<br>• Share something you are interested in<br>• Share your impressions with your friends<br>• React to what friends post<br>• Comment on what friends post<br>• Like what friends post | • Commenting on posts<br>• Share something on your wall<br>• Like what connections post. |

| Passive Consumption | |
|---|---|
| **Source** | **Adapted** |
| **Koroleva et al., 2011**<br>• Follow the news of your friends<br>• Look through the Newsfeed<br>• Click on the content shared by friends<br>• Browse the profiles of your friends<br>• Browse through friends of your friends<br>• Look at profiles of people not in the list | • Follow the news of your connections.<br>• Look through the News-feed.<br>• Click on the content shared by connections. |

<table>
<tr><th colspan="2">Perceived Social Connectedness</th></tr>
<tr><th>Source</th><th>Adapted</th></tr>
<tr><td><u>Krasnova and Veltri's (2010)</u><br>• feel close to the people in my contact list<br>• have a feeling of being connected to others<br>• am updated about my friends<br>• stay in touch with my friends<br>• keep contact with the people in my friend list<br>• interact with my friends more</td><td>On LinkedIn I<br>• Feel close to the people in my connection list.<br>• Have a feeling of being connected to others.<br>• Am updated about my connections.<br>• Stay in touch with my connections.<br>• Keep contact with the people in my connection list.<br>• Interact with my connections more</td></tr>
<tr><th colspan="2">Perceived Networking Value</th></tr>
<tr><th>Source</th><th>Adapted</th></tr>
<tr><td>Utz and Breuer's (2016) and Koroleva et al. (2011)<br>• I receive information about job opportunities from my network members.<br>• I receive information about innovations in my field from my network members, timely.<br>• My Facebook friends provide me with useful advice<br>• I turn to my Facebook friends when I need some information<br>• I can easily ask people in my contact list for a small favor<br>• I can easily ask my friends to put me in contact with someone<br>• The relationships that I maintain are helpful in making career moves.<br>• I can get access to knowledge that is helpful in mastering job tasks from my network members.<br>• Contacts that I have established are essential for my career success.</td><td>• I receive information about job opportunities from my LinkedIn connections/groups<br>• I get information about job market from my LinkedIn connections/groups<br>• Through my network connections on LinkedIn I can get easily valuable referrals.<br>• My LinkedIn connections elevate my social credentials in my field of work.<br>• Some of my LinkedIn connections/groups boost my identity and recognition.<br>• Information shared by my LinkedIn connections/groups is sufficiently timely.</td></tr>
</table>