Redirect your efforts: Extraversions effect on the informational benefits received from active and passive LinkedIn use.

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24-06-2021

Word count: 7855

Open for publication

Abstract

Online networking is facilitated by social networking sites (SNS). LinkedIn is an SNS used for professional purposes. Previous studies have shown that individuals can increase their social capital through LinkedIn by receiving information that they can use to improve their professional standing. This is because LinkedIn offers a unique networking experience as it satisfies all affordances in the affordance framework. The purpose of this study is to investigate how individuals receive these informational benefits from actively or passively using LinkedIn and how extraversion can moderate this relationship. Using an online survey, data was collected from 237 LinkedIn users. Active LinkedIn use and passive LinkedIn use both significantly positively predicted informational benefits. Extraversion significantly strengthened the relationship between active use and informational benefits, and significantly weakened the relationship between passive use and informational benefits. Post-hoc analyses suggest posting status updates and sending messages have the strongest relationship with informational benefits gained from LinkedIn. Both active and passive use of LinkedIn can be used to increase social capital and evaluating your level of extraversion can help redirect your efforts to a usage strategy that's more effective.

Keywords: informational benefits, social capital, active use, passive use, LinkedIn, extraversion.

Redirect your Efforts: Extraversions Effect on the Informational Benefits Received from Active and Passive LinkedIn Use.

Social Networking Sites (SNS) are online services that are defined by their ability to create personal public profiles, make connections with other profiles, and view one's connections as well as the connections of others (Davis, Wolff, Forret & Sullivan, 2020). The public display of connections is what distinguishes SNS from other online platforms. They allow users to visualize networks between themselves and others and easily browse these networks with just a few clicks. SNS facilitate networking through the creation of new connections and allow users to maintain and strengthen these relationships online (Badoer, Hollings & Chester, 2020). Networking behavior, even when performed online (Davis et al., 2020), can lead to significant career benefits (Forret & Dougherty, 2004), like information about job opportunities or coaching for better job performance (McCallum, Forret & Wolff, 2014). The resources held by individuals in a social network can be defined as social capital, and these resources can lead to a range of benefits, the most important for career success being informational benefits (McCallum, Forret & Wolff, 2014). Informational benefits are the access to work-related information and referrals that can be used for career opportunities. The central aim of this study is to investigate how individuals gain informational benefits from using certain SNS functions to network, and what factors influence this relationship.

Previous research on informational benefits and SNS use have applied the Social Capital Theory (SCT) as a central concept (Liu, Ainsworth & Baumeister, 2016; Utz, 2016; Utz & Breuer; 2016). The SCT contends that social relationships between individuals can create value and facilitate actions for individuals within social networks (Coleman, 1988. Previous research on social capital gained from SNS focuses on informational benefits. Informational benefits are the most common resources gained from professional networking (Utz, 2016). Some studies have looked at how individuals gain informational benefits by using different features of SNS (Davis et al., 2020; Utz 2016). Active use of SNS involves direct communication with other users or broadcasting. Direct communication includes communications targeted at a specific individual or group, such as sending a message, adding a contact, or commenting on a post. On the other hand, broadcasting is when a user writes a post not targeted to one individual but for all their network to view (Burke, Kraut & Marlow, 2011). This can include posting a status update or sharing a post to their newsfeed. Direct communication has shown increased informational benefits (Utz, 2016). The alternative form of SNS use is passive consumption (Burke, Kraut & Marlow, 2011), which involves only reading the communications or postings of others. While passive use has been shown to also lead to informational benefits, the effect is weaker compared to active use. Therefore, it would be greatly beneficial to better understand the factors that have an impact on this relationship. One such factor of interest is personality. Previous research has shown that the relationship between passive and active SNS use and informational benefits can be influenced by extraversion (Burke, Kraut & Marlow, 2011). Two competing hypotheses aim to explain the relationship between SNS use, social capital, and extraversion: the 'Rich Get Richer' hypothesis and the Social Compensation hypothesis. The 'Rich Get Richer' hypothesis claims that individuals with high levels of extraversion gain more social capital from SNS use due to their natural ability to be outgoing and sociable (Wastlund, Norlander & Archer, 2001). On the other hand, the Social Compensation hypothesis argues that individuals with lower levels of extraversion gain more social capital from SNS use, as what could be considered barriers to social interaction are lowered from behind a screen (Reer & Kramer, 2017). Therefore, those with low extraversion feel more comfortable in an online environment and more willing to interact with their networks.

While there is extensive literature on the strong positive relationship between networking and career success (McCallum, Forret & Wolff, 2014), few focus on online networking (Utz & Breuer 2016; Utz, 2016). Even though sites like LinkedIn are created to foster such networking interactions, the professional benefits of their use have not been explored in depth (Davis et al., 2020). Therefore, the research question of this study is: to what extent does extraversion moderate the relationship between active LinkedIn use and informational benefits, and the relationship between passive SNS use and informational benefits?

This study broadens the current academic literature by exploring the effects of extraversion on social capital gained from active and passive SNS use. Previous research has not thoroughly investigated this unique relationship. Moreover, this research holds practical relevance within the field of networking and SNS use. If a strong relationship between LinkedIn use and informational benefits is found, then individuals should focus their networking efforts towards online platforms. Additionally, understanding the moderating effect of extraversion will allow individuals to focus their efforts on specific functions of SNS in order to maximize their informational benefits. In conclusion, identifying the relationship between SNS use and the moderating role of extraversion can provide individuals with the tools to better prepare for career success by understanding how to utilize SNS.

Networking and SNS Use

The main focus of the current analysis is on the work-related online networking website LinkedIn. Networking behavior refers to "proactive attempts by individuals to develop and maintain relationships with others for the purpose of work or career benefits" (McCallum, Forret & Wolff, 2014; p. 2). Previous research on networking, including longitudinal studies, have shown that networking is strongly related to positive career outcomes, both objective and subjective, including compensation (Forret & Dougherty, 2004), career satisfaction (Wolff & Moser, 2009) and supervisor ratings of job performance (Thompson, 2005). Most studies investigating the use of SNS focus on Facebook (Zhang and Leung, 2015). While popular sites like Facebook and Twitter may facilitate professional networking, they are primarily used for personal purposes (Chou & Edge, 2012). Moreover, LinkedIn has a growing network of users; in 2021, 28% of adults said they use LinkedIn (Auxier and Anderson, 2021). LinkedIn is distinguished from other SNS by its professional purpose; LinkedIn is used not only for professional networking but also for recruitment and job-seeking purposes (Utz, 2016). The website provides individuals with the opportunity to create a professional identity and share career updates and history with other users. Furthermore, the website LinkedIn has been found to have become even more significant during the COVID-19 pandemic which saw a large number of individuals working from home. With this development, professionals were isolated from face-to-face networking events or casual networking during work (Bick, Blandin & Mertens, 2020). Thus, it is relevant to identify how LinkedIn use can lead to informational benefits and possible future career growth.

The public display of connections distinguishes SNS like LinkedIn from other online platforms, and allows users to visualize networks between themselves and others. Individuals can also traverse these networks with just a few clicks. For these reasons, SNS are a distinguished form of communication from other online communications like email, or face-to-face interaction. According to Leonardi and Treem (2012), SNS are a unique channel of communication because of the Affordance Framework. The Affordance Framework identifies four main elements: visibility, editability, association and persistence. SNS satisfy all four affordances while other forms of communication, like email, do not. Users on SNS like LinkedIn and Facebook, can openly share their knowledge and behavior with others with minimal effort (visibility) and have the ability to edit this information whenever they please (editability). Additionally, individuals can view information such as people's networks and which user is connected to whom (association). Finally, SNS also provide the ability to constantly review and record this information (persistence; Leonardi & Treem, 2012).

Social Capital Theory & Informational Benefits

According to Adler and Kwon (2002), social capital is "the goodwill available to individuals or groups. Its source lies in the structure and content of the actors' social relations. Its effects flow from the information, influence and solidarity it makes available to the actor" (p. 23). Therefore, social capital can be characterized as the resources one gains from their social network, including their online social network. These resources can vary and include the attainment of a social relationship that has value or facilitates further actions, like information or emotional support (Coleman, 1988). The SCT is commonly used to explain the benefits of using SNS for networking (Liu et al., 2016; Utz, 2016; Utz & Breuer; 2016). This theory is used as networking can improve individuals' social capital by expanding their social network and increasing the resources gained from their network (Reagans & Zuckerman, 2001), such as information about job opportunities. One of the critical social capital resources gained from networking is informational benefits (Liu et al., 2016), which is defined as the access to work-related information, such as advancements in one's field that can be used in work tasks. Informational benefits can also be defined as career opportunities, and referrals in a timely manner (Utz & Breuer, 2019).

The SCT assumes that informational benefits are gained from relationships with coworkers or acquaintances (Utz, 2016). These relationships are labelled weak ties, as they lack a strong personal bond between individuals. These types of relationships in a social network are characterized by a lack of deep affinity or emotional attachment (Obal, Burtch & Kunz, 2011). Most online social networks are made of up weak ties as these individuals have little to no in-person interactions and therefore lack a strong personal bond (Park, Gu, Leung & Konana, 2014). SNS are mainly catered towards these weak ties by allowing a high volume of weak tie connections and maintaining these relationships at minimal effort. Weak ties are also more likely to spread information than strong ties within a social network through word of mouth (Wang, Yeh, Chen & Tsydypov, 2016). Word of mouth communication is a form of casual information sharing between individuals within a social network and can lead to social capital in the form of informational benefits (Obal, Burtch & Kunz, 2011). The process of receiving social capital from weak ties within one's network is called social bridging (Burt, 1992). SNS provide a higher chance for social bridging due to the higher volume of weak ties and large amount of information available about those weak ties (Obal, Burtch & Kunz, 2011).

When investigating the effects of SNS on informational benefits, multiple studies have distinguished between active and passive SNS use (Utz, 2016; Utz & Breuer, 2016; Davis, et al., 2020; Burke, Kraut & Marlow, 2011). Active use of SNS consists of activities like posting status updates, commenting on others posts, sending direct messages and participating in groups. Previous research on active SNS use has shown it can contribute to informational benefits and therefore increase a user's social capital (Utz, 2016). SNS foster self-presentation by allowing users to actively create their own online profile and post what they want, which can then be viewed by others (Davis et al., 2020). This may facilitate trust for individuals seeing the post, either because frequent exposure increases trust and liking or because they are contributing online (Utz, 2016). This can increase social capital and informational benefits through knowledge sharing because people share with people they trust (McNeish & Mann, 2010). Knowledge sharing has been studied in relation to LinkedIn use. LinkedIn increases knowledge sharing due to increased sense of trust, sense of belonging and cooperation within individuals' online social network (Utz, 2016). Informational benefits gained from knowledge sharing can also increase individuals' chances of referral, either for promotions or job vacancies (Baruffaldi, Maoi & Landoni, 2017). It is therefore hypothesized in this study that active use will be positively related to informational benefits.

Hypothesis 1: Active LinkedIn use is positively related to informational benefits

Passive use consists of reading what others are posting, which can also lead to informational benefits (Utz & Breuer, 2016). This form of use can be intentional, like searching for answers to specific questions, or unintentional, like skimming the newsfeed and stumbling upon new information. Passive use, like looking at profiles of people within a user's organization or field, can allow a user to build a transactive memory; a cognitive structure for knowing who knows whom and who knows what within one's network (Jarvenpaa & Majchrzak, 2008). Passive use and the creation of a transactive memory can stimulate ambient awareness. Ambient awareness occurs when one is aware of the communications within their environment occurring amongst others (Leonardi, 2015). This knowledge can act as a social lubricant, making it easier to approach these individuals when interacting with them face-to-face (Leonardi & Meyer, 2015). Some researchers have hypothesized that regular passive use of SNS can create a sense of trust and lead to knowledge sharing between individuals (Fulk & Yuan, 2013; Utz, 2016). According to the SCT, knowledge sharing can increase informational benefits gained from one's network and therefore increase an individual's social capital (Widen-Wulff and Ginman, 2004). It is therefore expected that in this study, passive use will also be positively related to informational benefits.

Hypothesis 2: Passive LinkedIn use is positively related to informational benefits

Extraversion and SNS use

Another factor that has been shown to affect the social capital one gains from SNS use is the user's personality, particularly extraversion from the Five-Factor Model of Personality (FFM; McCrae & Costa, 1997). Of all the personality traits, extraversion has been shown to hold the strongest relationship with networking (Bendella & Wolff, 2019). An individual with a high level of extraversion refers to an individual who is sociable, outgoing and enjoys spending time surrounded by others (Mottus et al., 2020). Individuals low in extraversion are less sociable, quieter and prefer spending time on their own (Schmeck & Lockhart, 1983). The relationship between extraversion and networking has been shown extensively in studies of offline networking (McCallum, Forret & Wolff, 2014; Forret & Dougherty, 2001) and more recently in studies of online networking (Davis et al., 2020). Since extraverted individuals are considered to be more sociable, they find it easier to approach new people, create new connections and keep in contact with others (Forret, 2018).

Regarding internet usage, there are two competing hypotheses that explain the relationship between extraversion levels, online habits and social capital. These are the 'Rich Get Richer' hypothesis (Kraut et al., 2002) and the Social Compensation hypothesis (Poley & Luo, 2012). The 'Rich Get richer' Hypothesis, put forward by Kraut et al. (2001), reflects a social enhancement view of internet use, in that outgoing individuals with good social skills offline can use those same skills online to interact with others and make connections (Bouchillon, 2020). From these connections, they can then gain resources through social bridging. Extraverted individuals have been shown to have better outcomes from using the internet for communication, such as positive affect (Kraut et al., 2002; Lee, 2009) and increased social capital (Reer & Kramer, 2017). In some studies, individuals with low extraversion experienced negative effects from internet usage, like increased loneliness (Wastlund, Norlander & Archer, 2001). Peter, Valkenburg and Schouten (2005) found that individuals with high levels of extraversion had better chances of making friends online because they were more likely to actively participate by revealing personal information and communicating. This effect was also seen in a study by Reer and Kramer (2017) who found that individuals high on extraversion had higher levels of bridging social capital in an online interactive multi-player gaming platform when they were actively communicating with others.

The alternative Social Compensation hypothesis argues that the internet doesn't lead to increases in resources for extraverted individuals than it does for individuals with low extraversion. Extraverted people already have large networks that they benefit from, but people with low extraversion can take advantage of the anonymity and distance that the internet provides. These individuals can expand their network without being limited by their inhibitions or anxieties (Reer & Kramer, 2017). Hamburger and Ben-Artzi (2002) found that individuals with low levels of extraversion were able to express themselves socially on the internet more than individuals with high levels of extraversion. Moreover, it was also found that the intensity of SNS use was a strong predictor of creating new connections and social bonding for individuals with low social skills (Stenfield et al., 2012). The authors concluded that this was due to barriers being lowered by the SNS, which helped individuals who may have social difficulties. Further evidence of this was found in another study in which individuals with low social skills received better social capital and were more likely to make new connections when passively using Facebook and reading what others post (Burke, Kraut & Marlow, 2011).

Current Study

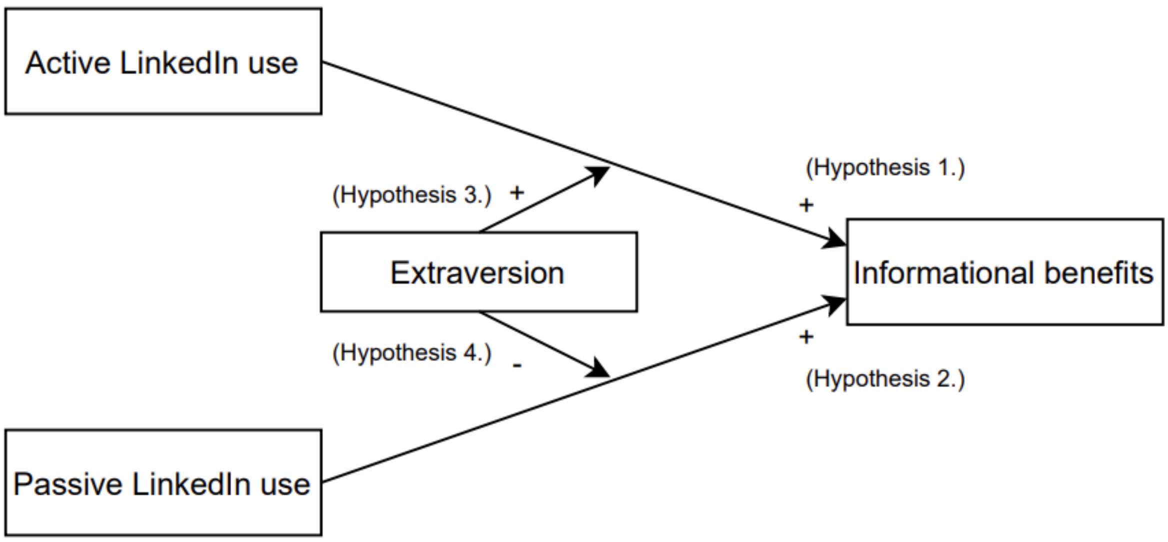
The results of these studies show that SNS usage is not always favorable for individuals with high levels of extraversion but may also be advantageous for individuals low in extraversion who need the barriers lowered in order to overcome inhibitions about networking (Reer & Kramer, 2017). One of the issues with past research is that it treats these two hypotheses, the ‘Rich Get Richer’ hypothesis and the Social Compensation hypothesis, as mutually exclusive. According to some of the previous studies mentioned, people with high levels of extraversion seem to gain more social capital from SNS use when they are actively participating (Peter et al., 2005; Reer & Kramers, 2017). Studies have also shown that people with low levels of extraversion gain more social capital when they are passively participating (Burke, Kraut & Marlow, 2011; Hamburger & Ben-Artzi, 2002). Therefore, the current study does not treat the two theories as mutually exclusive but suggests that an individual’s personality may influence how one receives social capital from the different types of SNS use. It is proposed that individuals with high levels of extraversion are more likely to receive social capital when they are actively participating, and individuals with low levels of extraversion are more likely to receive social capital when they are passively participating. In line with previous studies, active and passive use are considered independent of each other (Burke, Kraut & Marlow, 2011). For the purposes of this study, the social capital measured will be informational benefits, as it is the most relevant form of social capital to professional networking. Please refer to Figure 1 for a visual display of the conceptual model.

Hypothesis 3: The relationship between active LinkedIn use and informational benefits is moderated by extraversion in the way that the positive relationship is stronger when extraversion is high

Hypothesis 4: The relationship between passive LinkedIn use and informational benefits is moderated by extraversion in the way that the positive relationship is stronger when extraversion is low

Figure 1

Conceptual Model Illustrating the Proposed Relationships Between Active and Passive LinkedIn Use, Extraversion, and Informational Benefits of LinkedIn Users.



Methods

Participants

A power analysis was conducted using G*Power (3.2). A power of 0.8 was used, with a total of five predictors (active use, passive use, extraversion, active use*extraversion, passive use*extraversion) and an effect size of 0.05. The power analysis revealed an estimate of 187 participants needed for the sample size.

In total 234 participants responded to the online survey. The participants answered all questions. Of these participants 140 (59.1%) were female, 93 (39.2%) were male and 1 preferred not to disclose their gender (0.4%). All participants were between the ages of 20 and 70 years (*M* = 29.4, *SD* = 11.9). The most common highest level of education completed was a bachelor's degree (60.7%) and the second most common was a master's degree (32.5%). 29.9% of participants were seeking new employment. 20.5% of participants were unemployed, 71% were employed in a company and 8.5% were self-employed.

Procedure

Data was collected through an online survey. This method was chosen for its ability to reach a large amount of people and collect data on all variables at once. The study was approved by the University of Utrecht's Ethical Review Board and their protocol for online surveys was followed. All data collected in the survey was anonymous. As the research is concerned with the SNS LinkedIn, the survey was distributed throughout a variety of different channels on LinkedIn. The study aims to generalize the received responses to the general population of LinkedIn users.

The online survey was designed using the program Qualtrics (Qualtrics XM, 2019) which also collected the raw data (see Appendix A). Participants were able to respond to the survey using any device with an internet connection. Participants were asked to have their LinkedIn account at the ready, either on a separate device or on another tab, to retrieve the exact information needed for assessing their LinkedIn profile.

Measures

Demographics & Organizational variables

The survey began by asking demographic questions; age, gender, highest level of education completed, and employment status. Organizational variables were also measured. These were years in current position, years of work experience, weekly working hours and current position level. These measures are to gain an understanding of the sample used.

Extraversion

Extraversion was measured using eight items from Big Five Inventory (BFI; John & Srivastava, 1999), specifically the eight items that measure extraversion. Participants provided their answers on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree". An example item on this measure is "I am talkative" and an example reverse score item is "I am reserved". In this current study an internal consistency of .91 and an average inter item correlation of .56 was measured for this scale.

Informational benefits

Informational benefits were measured using five items from the scale by Wickramasinghe and Weliwitigoda (2011): "I can gain access to knowledge that is helpful in mastering job tasks from my network members", "I receive information about innovations in my field from my network members, timely", "Contacts that I have established are essential for my career success”, “The relationships that I maintain are helpful in making career moves” and “I receive information about job opportunities from my network members”. Participants were asked to indicate how much they agree with each statement on a 5-point Likert scale ranging from “strongly disagree” to “strongly agree”. The score for each item was added to compute the total variable: informational benefits. Informational benefits were measured as a single variable, as previous studies have shown that these items load onto a single factor that explains 73% of the variance. (Utz, 2016). In this current study an internal consistency of .85 was measured with an average inter-item correlation of .52.

Active and Passive SNS Use

Prior studies investigating active and passive SNS use have used the number of connections and frequency of login to measure active use and passive use, respectively (Burke, Kraut & Marlow, 2011; Utz, 2016). Due to this study’s focus on LinkedIn, a wider range of variables based on participants LinkedIn profiles and their self-reported LinkedIn use was also recorded. This was recorded to gain a better understanding of participants LinkedIn use by using observable figures as well as self-reported behaviors.

The first range of variables collected were based on the scale used by Davis et al. (2020), which measured LinkedIn variables under the control of the user. These variables were: if the user had a profile photo posted, their number of connections, their number of endorsements received, their number of groups they are a member of, the number of pages they are following and the number of influencers they are following. Participants were instructed how to find the exact figures from their LinkedIn profile while they were completing the survey. Davis et al. (2020) also measured number of causes following, number of volunteer organizations following, and number of recommendations received. These three variables were omitted from this research to prevent survey drop out as they are harder to access accurately without direct access to participants accounts. The five variables used from this scale –connections, groups, endorsements, companies following and influencers following – were log transformed because they were highly skewed. Zero counts were included by adding one to all data points (Davis et al., 2020).

According to the principled components analysis conducted in the study by Davis et al. (2020), the first four variables (profile photo, connections, endorsements, and groups) measured active use while the latter two (pages and influencers following) measured passive use along with frequency of login (Davis et al., 2020). Although frequency of login was self-reported, prior studies have found this variable shows extremely low levels of bias and is reliable (Burke at al., 2010).

Finally, LinkedIn activity was further measured using an adapted scale by Ma and Leung (2018). This scale measured how often participants use each of the 16 primary features on LinkedIn. Participants answered on a 5-point Likert scale ranging from “Never” to “Always”. Example items included “Add new contacts”, “Follow influencers” and “Leave likes on posts by users/contacts”.

Principal component analysis. To investigate the underlying structure of these scales and how accurately they can measure the desired variables (active LinkedIn use and passive LinkedIn use) a principal component analysis was performed with a fixed number of factors (2). As it is assumed that the factors are correlated (Davis et al., 2020), an oblique rotation (direct oblimin) was used. The Kaiser-Meyer-Olkin (KMO) test for adequacy revealed the sample was meritorious for factor analysis (KMO = .88). A two-factor extraction was used to divide all items into either active or passive (see Appendix B, Table B1 unstandardized regression coefficient for factor loadings). These two factors explained a cumulative 56.1% of the variance. Only one variable did not load significantly on to either factor: photo posted. This variable was removed, as it did not correlate above .3 with either factor or the scale overall (Field, 2013). It is hypothesized that this variable does not significantly indicate active or passive LinkedIn use, as most people who have a LinkedIn account will post a profile picture as they are creating their account (90.7% of participants in this study had a profile picture posted on their LinkedIn account). The principal component analysis, with a fixed number of two factors, was repeated with the “profile picture posted” variable removed (see Appendix B, Table B2 for factor loadings).

After removing the “photo posted” item the two factors explained 58.4% of the variance. Factor 1 contained items including “number of connections”, “number of endorsements”, and “update my status”. As all the items on this factor involve direct communication or broadcasting it was labelled “active use”. Factor 2 contained items including “number of companies following”, “frequency of login” and “read pages/influencers”. As all these items involve reading and passive consumption of information posted by others it was labelled “passive use”. A reliability analysis was conducted on each factor. “Active use” had 16 items, a Cronbach’s Alpha Based on Standardized Items of .95 (due to variety in response between items), and an average inter-item correlation of .53. “Passive use” had six items, a Cronbach’s Alpha Based on Standardized Items of .84, and an average inter-item correlation of .46. Component scores for active use and passive use were computed by standardizing the scores for each variable and averaging these scores across each component. A Pearson's correlation showed no significant correlation between active and passive LinkedIn use (r = .03, p > .05).

Statistical analysis

The data was analyzed using the Statistical Program for Social Sciences (SPSS). Common method variance was assessed using a Harman's Single Factor test. A single factor confirmatory factor analysis using all items in the scales for the four model variables (active LinkedIn use, passive LinkedIn use, extraversion, and informational benefits) showed the maximum variance explained by a single component was 28.76%. As this number is less than 50%, it is concluded that there is no common method bias presented and there is independence among the measurements (Eichhorn, 2014).

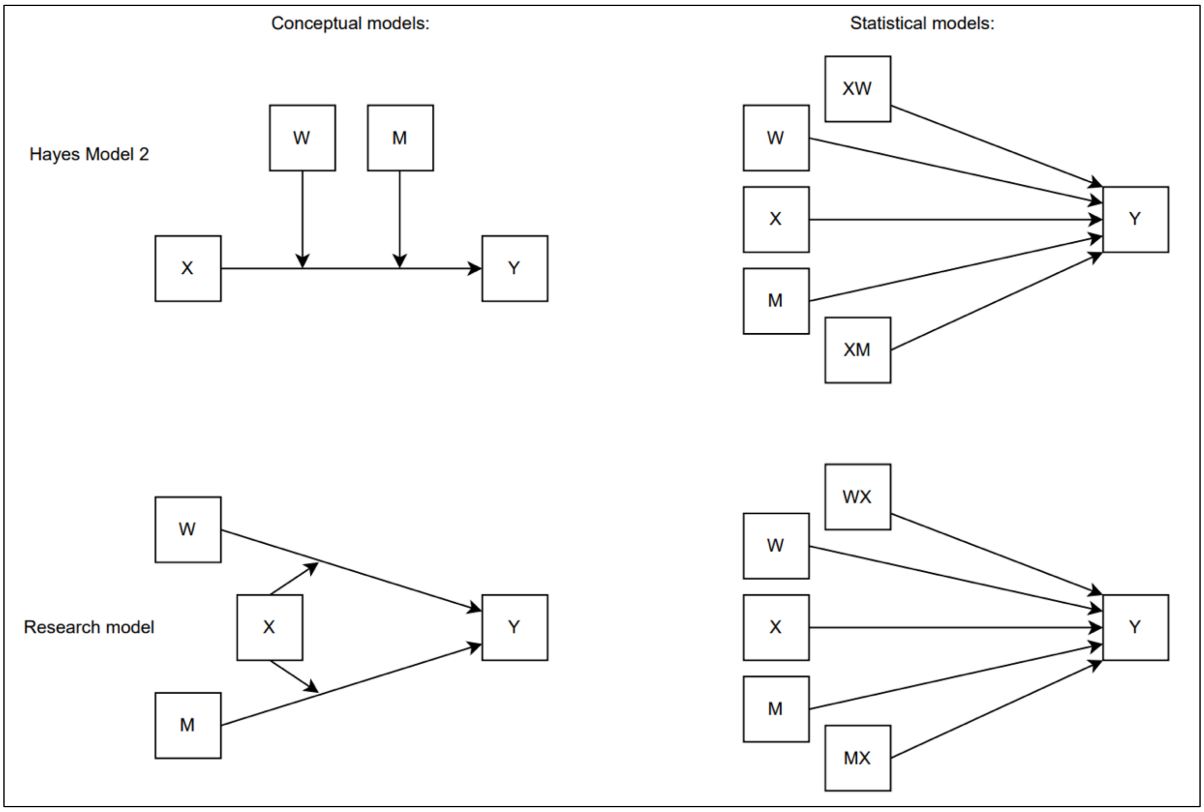
All scales were then assessed for the assumptions underlying multiple regression. There were no significant outliers and scatter plots revealed linearity between the dependent variable and each of the independent variables. There was homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. There was an absence of multicollinearity (VIF<10). Normal P-P Plots showed normality. There was independence of residuals, as assessed by a Durbin-Watson statistics of 1.913.

Before conducting the main analysis, a correlation matrix was used to determine any significant effects between the variables. The moderation analysis used is a multiple regression to estimate the amount of variance in informational benefits that can be explained by the independent variables: active LinkedIn use, passive LinkedIn use and extraversion.

A moderation analysis was conducted using Hayes' (2017) PROCESS Version 3.5.3. add on in SPSS. Model 2 with 95% CI and 5000 bootstrap samples was used. While Model 2 does not conceptually match the model used in this study (see Figure 2), the statistical model is the same. Therefore Model 2 was chosen, and the entire conceptual model was tested in one analysis. This was to avoid running two separate analyses for both moderations and having to control for the other independent variable. The research model was tested in one analysis, where the two independent variables (active LinkedIn use and passive LinkedIn use) were set as moderators W and M, and the moderator (extraversion) was set as the independent variable X. Informational benefits remained as the dependent variable Y. The variables were mean centered in the analysis to facilitate the interpretation of the results (Hayes, 2017). The p-value was set at .05.

Figure 2

Comparison of the Tested Conceptual Model and the Hayes Model 2



Results

Descriptive statistics

Table 1. shows an overview of study variables and their range, means, standard deviations and intercorrelations. The variables age and highest level of education completed showed a strong positive relationship. Age also showed a strong positive relationship with active LinkedIn use and highest level of education completed showed a strong positive relationship with both active LinkedIn use and passive LinkedIn use. As for the variables in the model, informational benefits showed significant positive relationships with both active LinkedIn use and passive LinkedIn use. Extraversion showed a strong positive relationship with active use and a significant negative relationship with passive use.

Table 1.

Range, Means, Standard Deviation and Correlation Coefficients of Study Variables (N=234).

	Range	M	SD	1	2	3	4	5	6
1. Gender[a]	1-2	1.61	0.51						
2. Age[b]	20-70	29.38	11.92	-0.13					
3. Education[c]	2-5	3.44	0.69	-0.05	0.34**				
4. Informational Benefits	5-25	18.78	4.18	0.04	0.04	0.11			
5. Extraversion	10-40	28.55	7.20	-0.03	0.07	0.01	0.12		
6. Active LinkedIn Use	-1.56 -1.87	-0.17[d]	0.75	-0.01	0.32**	0.19**	0.43**	0.26**	
7. Passive LinkedIn Use	-1.59-1.82	0.003[d]	0.74	-0.01	0.11	0.15*	0.20**	-0.15*	0.03

Note. *p<.05, **p<.001

[a]1 = male, 2 = female, [b]in years, [c]highest level of education completed in categories: 2 = secondary school, 3 = bachelor's degree, 4 = master's degree and 5 = doctoral degree, [d]mode is reported instead of mean due to standardized scales

Hypothesis Testing

Main Effects

The entire conceptual model was tested in one analysis using Model 2 of the Hayes PROCESS add on for SPSS. The overall model with all five predictors was significant, with the variables in the model predicting 41.51% of the variance in informational benefits, F(5, 220) = 31.22, p <.001, R^2 =.42. Active use has a significant positive relationship with informational benefits, t(220) = 5.91, p < .001 (see Table 2). This supported hypothesis 1, that active LinkedIn is positively related to informational benefits. Passive use also showed a significant positive relationship with informational benefits, t(220) = 2.76, p <.01. This supported hypothesis 2, that passive use is positively related to informational benefits.

Table 2.

Regression Coefficients, SE, t, and p values for the Predictors of Informational Benefits

			Informational Benefits			
		R^2	β	SE	t	*p*
Hypothesis 1	Active Use		2.1786	.3684	59.135	.0000
Hypothesis 2	Passive Use		.8759	0,3169	2,7645	.0062
Hypothesis 3	AU*Extraversion	.0483	.2149	0,0504	42.603	.0000
Hypothesis 4	PU*Extraversion	.0415	-.1467	0,0371	-39.527	.0001

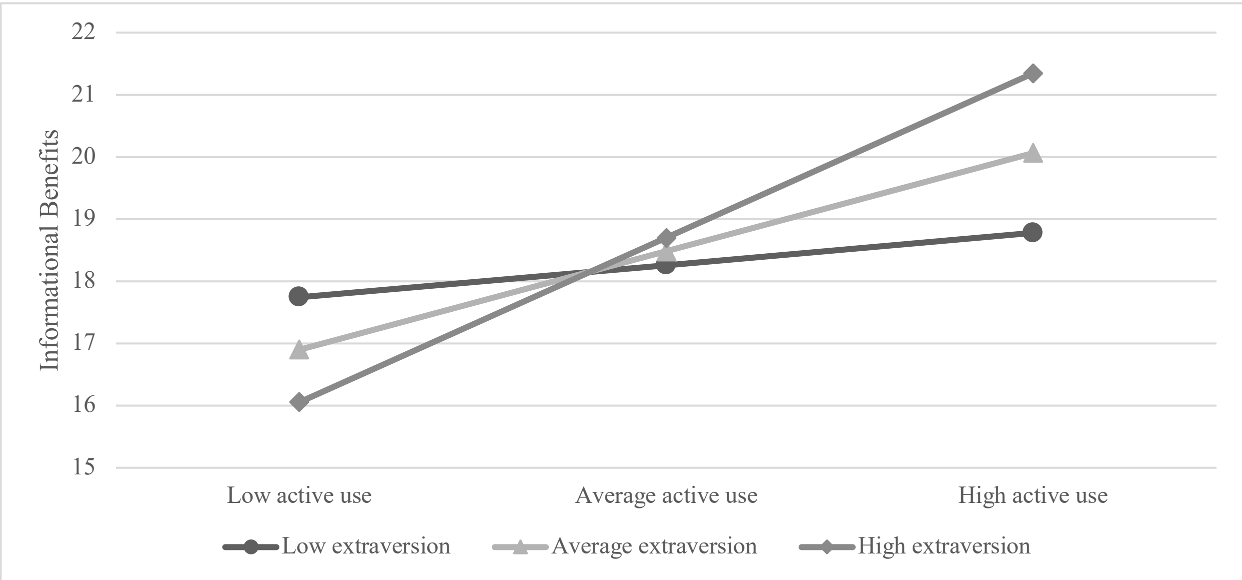
Note: β = unstandardized regression coefficient, SE = standard error, t = t value, *p* = *p* value

Interaction effects

The interaction of extraversion and active use significantly predicted informational benefits, t(220)=4.26, $p<.001$, such that when extraversion was high and active use was high, information benefits were higher (see Figure 3 and Appendix D). The addition of the interaction significantly increased the variance explained by the overall model, F(1, 220)=18.15, $p<.001$, $R^2 = .05$ This supports hypothesis 3, that extraversion moderates the relationship between active use and informational benefits in a way that when extraversion is high, the positive relationship is stronger. The addition of the interaction of active LinkedIn use and extraversion accounted for 4.83% of the added variation in informational benefits.

Figure 3.

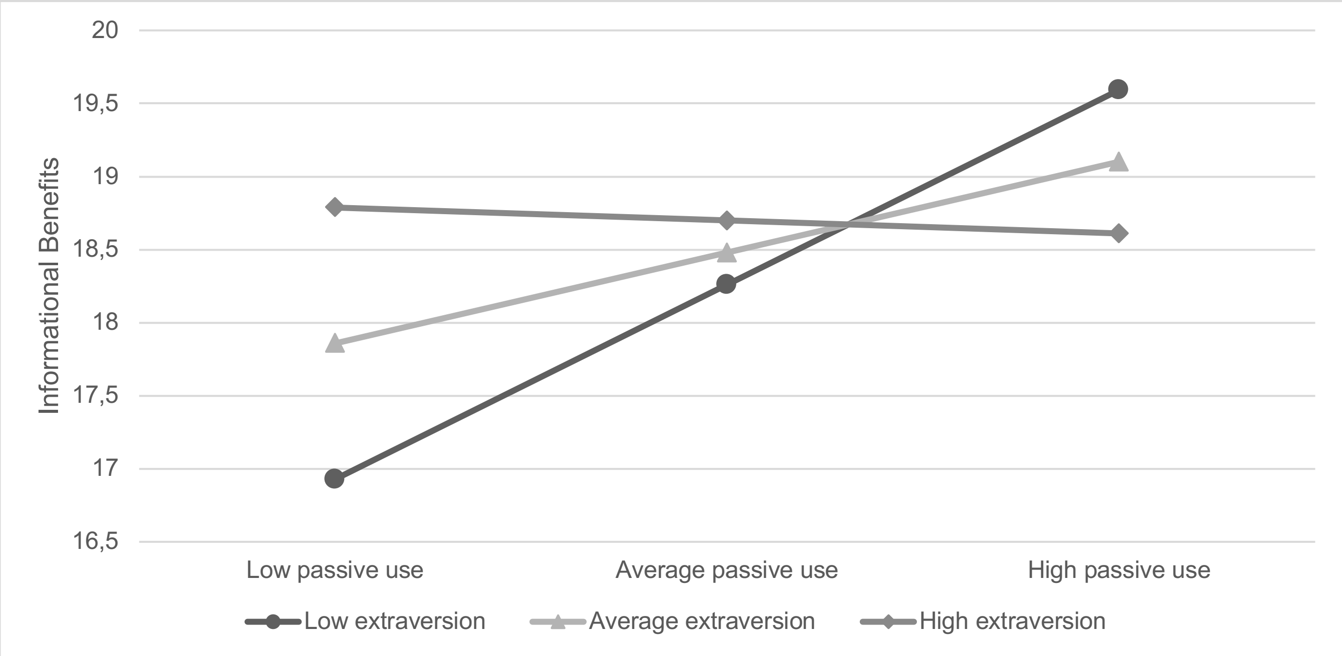
Moderation of the effect of active use on informational benefits at low, average, and high levels of extraversion



The interaction of extraversion and passive use significantly predicted informational benefits, t(220)=-3.95, $p<.001$, such that when extraversion was low and passive use was high, informational benefits were higher (see Figure 4). The addition of this interaction also significantly increased the amount of variance explained by the overall mode, F(1, 220)=15.62, $p<.001$, R^2 change=.04. The effect for this relationship was negative ($\beta = -.14$), meaning that when passive use was high and extraversion was low, informational benefits were higher. This supports hypothesis 4, that extraversion moderates the relationship between passive use and informational benefits in a way that when extraversion is low, the positive relationship is stronger. The addition of the interaction of passive LinkedIn use and extraversion accounted for 4.15% of the added variation in informational benefits

Figure 4.

Moderation of the effect of passive use on informational benefits at low, average, and high levels of extraversion



Post-Hoc Analyses

An additional correlation matrix was run to assess the relationship between informational benefits and the individual items of the active and passive scales (see Appendix C, Table C1) This test was run to see if there was any indication that specific LinkedIn variables or features of use have a significant relationship to informational benefits. Most of the variables and features had significant positive correlations with informational benefits, except for number of endorsements and reading group pages. Updating status or activities on one's homepage has the strongest correlation with informational benefits (r = .39), followed by sending messages to contacts or other users (r = .38). The items with the smallest yet significant correlation were number of companies following (r = .14), following company/influencer pages (r = .13), and reading company/influencer pages (r = .13). These three items were part of the passive LinkedIn use scale. Even though number of connections had significant positive correlation with informational benefits (r = .17), this was correlation was smaller than frequency of login (r = .24) and number of groups (r = .25) with informational benefits. Number of endorsements had no correlation to informational benefits ($r = .09$) but seeking endorsements did ($r = .30$).

Discussion

This study investigated the relationship between LinkedIn use and informational benefits, and moderating effect of extraversion on this relationship, in a sample of 234 LinkedIn users. The central question to this research was: *How does an individual's level of extraversion influence how informational benefits are received from active and/or passive LinkedIn use?*

Interpretation of results

All four of the hypotheses to test the conceptual model were supported by the statistical analysis. In line with previous research (Davis et al., 2020; Utz, 2016; Utz & Breuer, 2016), active LinkedIn use was positively related to informational benefits, supporting hypothesis 1. Also, consistent with previous research, passive LinkedIn use was positively related to informational benefits (Utz, 2016; Utz & Breur, 2016, Fulk & Yuan, 2013), supporting hypothesis 2. Results therefore showed that any form of LinkedIn use can lead to an increase in informational benefits. The relationship between active LinkedIn use and informational benefits was stronger than the relationship between passive use and informational benefits, which is also shown in past research (Utz & Breuer, 2016; Davis et al., 2020).

This study also examined how the relationships between LinkedIn use and informational benefits are influenced by an individual's level of extraversion (hypothesis 3 & 4). Based on previous research on how extraversion influences how individuals gain social capital from online networking, it was expected that extraversion moderates both relationships differently. Hypothesis 3 predicted that extraversion strengthens the positive relationship between active LinkedIn use and greater informational benefits. This is in line with the 'Rich Get Richer' hypothesis, which suggests that high levels of extraversion can lead to increase social capital from online networking (Kraut et al., 2002; Reer & Kramer, 2017). This was supported by the statistical analysis, such that when individuals with high extraversion were actively using LinkedIn, their informational benefits were higher. Hypothesis 4 predicted that extraversion weakens the positive relationship between passive use and informational benefits. This hypothesis was supported by the Social Compensation hypothesis, which suggests that individuals low in extraversion gain more social capital from online networking (Hamburger et al., 2002; Reer & Kramer, 2017). This theory was supported in the current analysis, as individuals with low levels of extraversion passively using LinkedIn also reported higher information benefits.

Post-hoc analyses were also conducted to examine further the specific LinkedIn features and how they relate to informational benefits. Correlations showed that posting a status update and sending a message to another contact or user had the strongest relationship with informational benefits. These were both items on the “active LinkedIn use” scale, which is in line with previous research that active use holds the stronger relationship with informational benefits (Davis et al., 2020; Utz & Breuer, 2016). This is further supported by the items with the smallest significant relationship to informational benefits: the number of companies and influencers following. These are both items on the “passive LinkedIn use” scale and while they too have a significant positive relationship with informational benefits, the effect is smaller than active use. However, these results must be interpreted with care as they do not represent a causal relationship. It may be that individuals with high informational benefits feel more knowledgeable and confident to share information in status updates and messages, hence the positive relationship.

Theoretical implications

The theoretical implications of the findings from this research are discussed. The results from this study expands upon literature by showing that the ‘Rich Get Richer’ hypothesis and the Social Compensation hypothesis are not necessarily mutually exclusive. Instead of providing a simple answer of whether individuals with high or low extraversion gain more social capital from online networking, this study provides a nuanced analysis of how these different groups gain social capital from online networking. The previously held idea that these two theories are exclusive processes underlying SNS use is challenged.

In line with the ‘Rich Get Richer’ hypothesis, individuals with high levels of extraversion gained greater informational benefits from SNS use. This interaction occurred when individuals were actively using the site LinkedIn. According to this hypothesis, individuals with high levels of extraversion are able to gain more social capital due to their ability to leverage their existing social skills and resources in an online environment. This is supported by the results in this study, where individuals with high active use and a high level of extraversion had the largest number of informational benefits. Therefore, when using the features on LinkedIn that involve direct communication or broadcasting, outgoing individuals with social skills can increase their social capital.

The results from this study also showed support for the Social Compensation hypothesis, which posits individuals with low extraversion gain more social capital due to the lowering of social barriers. The research showed support for this, in that when individuals were passively using LinkedIn and had low extraversion, their informational benefits were higher. Therefore, when individuals who had fewer social skills and preferred spending time on their own read information on LinkedIn, they were able to increase their social capital. This may be due to the creation of a transactive memory or an increase in ambient awareness. Passive use and ambient awareness have been shown to increase informational benefits by acting as a social lubricant for face-to-face interactions (Leonardi & Meyer, 2015). This could explain the weaker relationship with passive use and informational benefits in this study, as individuals couldn't gain benefits from their ambient awareness due to COVID-19 preventing face-to-face interaction. Future research could benefit from investigating further the mechanisms behind passive SNS use and its benefits.

Active and passive use have previously been measured using the number of connections (active) and frequency of login (passive). The results of this study revealed that number of connections did not have as strong a positive relationship with informational benefits as frequency of usage. This is contrary to previous studies, which generally show that the number of connections is the stronger predictor (Burke, Kraut & Marlow, 2011). The results still support previous studies on weak ties (Obal, Burtch & Kunz, 2011), which states that weak ties in an individual's social network led to social capital through increased chance of social bridging. It could be that number of connections may not accurately measure weak ties, as individuals could be adding new contacts for the sole purpose of increasing their number of connections. It may also be that with the continuous development of SNS and their use features, number of connections and frequency of usage are not sufficient measures of active and passive SNS use. The inclusion of LinkedIn variables as well as self-reported LinkedIn usage is therefore considered a strength of this current research.

Practical implications

The results of this research have multiple practical implications. Firstly, this study found that practically any use of LinkedIn is related to increased informational benefits. Both active and passive participation were shown to have a significantly strong positive relationship with informational benefits. The only items on the scales which did not show significant correlations with informational benefits were number of endorsement and reading group pages. It is therefore suggested that individuals looking to increase their social capital through informational benefits create and use a professional LinkedIn profile. This is particularly important for individual who may not have access to in person networking events, and therefore must focus their efforts on online networking.

The significant interaction effects in this study show that an individual's level of extraversion can influence the informational benefits retrieved from LinkedIn, dependent on how they are using LinkedIn. Individuals may be able to better focus their networking efforts by directing their attention to either active or passive use, depending on their level of extraversion. Individuals with high levels of extraversion should focus on active participation, posting status updates, leaving comments, and sending messages. Individuals who have lower levels of extraversion may prefer to increase their informational benefits by reading more on the timeline and following more pages.

Limitations and directions for future research

This study had several limitations that should be acknowledged. First, this study may have issues with generalizability. The participants in this study were highly educated, with the vast majority having completed higher education. It is therefore unknown if LinkedIn has strong effects on informational benefits or if this population is more likely to receive informational benefits from any form of online networking. Future studies would benefit from a wider range of educational histories and backgrounds.

Secondly, this study only investigated the effects of active and passive use of LinkedIn, as opposed to multiple other SNS which could be used for professional networking. It could therefore be difficult to generalize the theoretical findings to other SNS. Future studies may also benefit from investigating active and passive use of other SNS, like Facebook and Instagram, and comparing the informational benefits received with those from LinkedIn. This would allow for a wider sample of individuals who are not LinkedIn users, but still use SNS for professional purposes.

Thirdly, this study collected data from a single point in time using self-report measures. Future research should consider a longitudinal study design to assess how LinkedIn behaviors lead to informational benefits over time. It would be useful to see how quickly one can receive informational benefits from actively or passively using LinkedIn. Even though some of the LinkedIn variables measured in this study were based on observable numbers from individuals LinkedIn profiles, the behaviors were measured by self-report. A longitudinal study could implement a more accurate way of tracking LinkedIn behavior, such as a diary. Future research could also benefit from measuring more non-self-report career outcomes of active and passive LinkedIn use, such as job opportunities, promotions, or salaries. It would also be interesting to see at what career stage these effects are most prominent. Does LinkedIn use lead to more benefits when you are unemployed and searching for an entry-level job? Or is it more useful when trying to get a promotion in the later stages of one's career?

Finally, this study analyzed data regarding use of SNS during a time in which individuals are spending a lot of time online. Since the COVID-19 pandemic, individuals have had to shift their networking efforts from face-to-face interaction to the internet. Therefore, there may be issues with generalizability. How will the effects found in this study translate if face-to-face networking becomes the norm again? Passive consumption may lead to more benefits when one can use the information gained to lower social barriers in face-to-face interaction. Future studies should compare in-person and online networking to see which, or what combination of both, is the most effective in receiving social capital from one's network.

Conclusion

While adding to the growing literature on online networking, the results from this study show that a user's level of extraversion can influence how informational benefits are received from the SNS LinkedIn. Both active and passive use of LinkedIn can increase a user's informational benefits. A high level of extraversion will increase informational benefits when a user is actively using LinkedIn, and a low level of extraversion will increase informational benefits when a user is passively participating. Individuals looking to increase their social capital should create and foster a LinkedIn account for professional purposes. Technology can lead to career success, and further investigation into how is needed.

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Appendix A: Questionnaire

Introduction

Dear Participants,
Have you ever wondered if using LinkedIn is actually helping you network? And if so, how? By taking part in this thesis project, you can help us find the answers!
The aim of the study is to investigate how the ways in which people use LinkedIn affect how they collaborate with others in their network.
In this survey, you will be asked a variety of questions regarding your experience using LinkedIn. You will be presented with a variety of statements, which you will be asked to indicate how much you agree with these statements. Please answer as honestly as possible, there are no right or wrong answers. The duration of this survey is around 7 minutes (max.10). It would be helpful for some of the questions to **have your LinkedIn profile open in another tab or on your phone**.
All answers given in this survey are anonymous. Any data received will not be traceable back to you and will only be used by the main researcher when analyzing the sample of data as a whole. You have the right to remove yourself from this study at any point for any reason and if so, your data will be discarded.
For info & concerns; contact me at d.e.aikins@students.uu.nl.
Informed consent:
By clicking "I consent" you confirm you have read the information above and acknowledge that your participation in the study is voluntary, you are at least 18 years or older, and you have the right to withdraw from the study at any point for any reason. You agree to the anonymous collection of your data. If you do not click "I consent" your participation in the study will be terminated.

- I consent

What is your gender?

- Male
- Female
- Prefer not to say
- Other

How old are you? (in whole numbers)

What is the highest level of education you have completed?

- Primary education
- Secondary education
- Bachelor's degree
- Master's degree
- Doctoral degree
- Other

Which of the following statements applies to you?

- I am currently employed, seeking new employment
- I am currently employed, not seeking new employment
- I am currently self employed
- I am unemployed not seeking employment
- I am unemployed seeking employment

Instructions: For the following questions, please give your answers rounded to the nearest whole number. If you have more than one job, please answer regarding the position you work in more frequently. If you are unemployed please answer regarding your most recent employment.

If you have never been employed then please answer "0" and "Other".

How many years have you been working in your current organization?

How many years have you been working in your current position within your organization?

How many years of work experience do you have in total?

How many different organizations have you previously worked for?

How many hours do you work in your current position, on average every week?

What is the level of your current position within your organization?

- Operational level
- Managerial level - middle manager
- Managerial level - senior manager
- Executive level
- Other/not applicable

Instructions: In this section you will be asked questions about your usage of the professional networking site ‘LinkedIn’. For this section, it would be helpful to have your profile ready in a separate tab or on your phone so you can accurately answer each question.

[NOTE: The number of endorsements can be found on your profile, near the bottom of the page under “Skills & Endorsements”. The number of connections, organisations followed, influencers followed and groups can be found in the “My Network” section under “Manage my network”.]

Please answer in whole numbers.

Frequency of login How often do you use Linkedin?

- Daily
- 2-3 times a week
- Once a week
- 2-3 times a month
- Rarely

LinkedIn picture Do you have a profile picture posted on LinkedIn?

- Yes
- No

How many connections do you have on LinkedIn?

How many groups are you a member of? (My Network -> Manage My Network -> Groups)

How many companies/organisations do you follow? (My Network -> Manage My Network -> Pages)

How many influencers do you follow? (My Network -> Manage My Network -> People I Follow)

How many endorsements do you have? (Me -> View profile -> Skills & Endorsements)

For the following statements, please indicate how often you use these LinkedIn features from "never" to "always".

1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Always

On LinkedIn I...

- Forward/share posts published by contacts or other users
- Forward/share posts published by companies, influencers, or other groups/channels
- Leave likes on posts published by companies, influencers or other groups/channels
- Leave likes on posts published by contacts/users
- Leave comments on posts published by contacts/users
- Leave comments on posts published by companies, influencers or other groups/channels
- Follow companies or influencers
- Read company/influencer pages
- Join groups/channels
- Read group pages
- Update my current status or activities on my homepage
- Update or refine my profile
- Seek recommendations or endorsements
- View others profiles
- Add new contacts

- Send messages to contacts or other users

Here are 5 statements that may apply to you and your network. Your network refers to personal and professional relationships you hold, whether they are weak or strong. When answering these questions, please refer to your LinkedIn network.

Please indicate the extent to which you agree or disagree with these statements.

1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, 5 = Strongly agree

- I can gain access to knowledge from my network members, that is helpful in mastering job tasks
- I receive information about innovations in my field from my network members, in a timely manner
- Contacts that I have established are essential for my career success.
- The relationships that I maintain are helpful in making career moves.
- I receive information about job opportunities from my network members.

Here are a number of characteristics that may apply to you. Please indicate the extent to which you generally agree or disagree with each statement.

1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, 5 = Strongly agree

I see myself as someone who...

- Is talkative
- Is reserved
- Is full of energy
- Tends to be quiet
- Has an assertive personality
- Is sometimes shy, inhibited.
- Is outgoing, sociable
- Generates a lot of enthusiasm

Appendix B. Principal Component Analyses

Table B1.

Principal Components Solution for Two-Dimensional Solution of All Items Measuring LinkedIn Use

	Factor 1 Active use	Factor 2 Passive use
Number of connections	**0.39**	0.13
Photo posted	**0.20**	-0.14
Number of groups	**0.68**	-0.04
Number of endorsements	**0.43**	0.17
"Forward/share posts published by contacts or other users"	**0.87**	-0.09
"Forward/share posts published by companies, influencers, or other groups/channels"	**0.85**	-0.09
"Leave likes on posts published by companies, influencers or other groups/channels"	**0.72**	0.18
"Leave likes on posts published by contacts/users"	**0.77**	0.18
"Leave comments on posts published by contacts/users"	**0.85**	-0.05
"Leave comments on posts published by companies, influencers or other groups/channels"	**0.82**	-0.05
"Join groups/channels"	**0.63**	0.39
"Update my current status or activities on my homepage"	**0.79**	-0.09
"Update or refine my profile"	**0.74**	-0.01
"Seek recommendations or endorsements"	**0.75**	-0.20
"View others profiles"	**0.55**	0.22
"Add new contacts"	**0.80**	0.10
"Send messages to contacts or other users"	**0.81**	0.02
Frequency of login	0.12	**0.59**
Number of companies/pages following	0.03	**0.53**
Number of influencers/people following	-0.04	**0.44**
"Follow companies or influencers"	-0.17	**0.84**
"Read company/influencer pages"	-0.24	**0.82**
"Read group pages"	-0.10	**0.73**

Rotation Method: Oblimin

Note: N = 234. Factor loadings > 0.30 are in boldface.

Table B2.
Principal Component Solution for Two-Dimensional Solution of LinkedIn Use With the iIem "Photo Posted" Removed.

	Factor 1 Active use	Factor 2 Passive use
Number of connections	**0.41**	0.12
Number of groups	**0.68**	-0.09
Number of endorsements	**0.43**	0.13
"Forward/share posts published by contacts or other users"	**0.86**	-0.15
"Forward/share posts published by companies, influencers, or other groups/channels"	**0.84**	-0.15
"Leave likes on posts published by companies, influencers or other groups/channels"	**0.73**	0.13
"Leave likes on posts published by contacts/users"	**0.78**	0.13
"Leave comments on posts published by contacts/users"	**0.85**	-0.11
"Leave comments on posts published by companies, influencers or other groups/channels"	**0.81**	-0.11
"Join groups/channels"	**0.66**	0.33
"Update my current status or activities on my homepage"	**0.77**	-0.14
"Update or refine my profile"	**0.74**	-0.04
"Seek recommendations or endorsements"	**0.73**	-0.25
"View others profiles"	**0.57**	0.18
"Add new contacts"	**0.80**	0.05
"Send messages to contacts or other users"	**0.81**	0.04
Frequency of login	0.17	**0.58**
Number of companies/pages following	0.07	**0.53**
Number of influencers/people following	-0.08	**0.44**
"Follow companies or influencers"	-0.09	**0.85**
"Read company/influencer pages"	-0.18	**0.84**
"Read group pages"	-0.04	**0.73**

Rotation Method: Oblimin
Note: N = 234. Factor loadings > 0.30 are in boldface.

Appendix C: Post-hoc Analysis

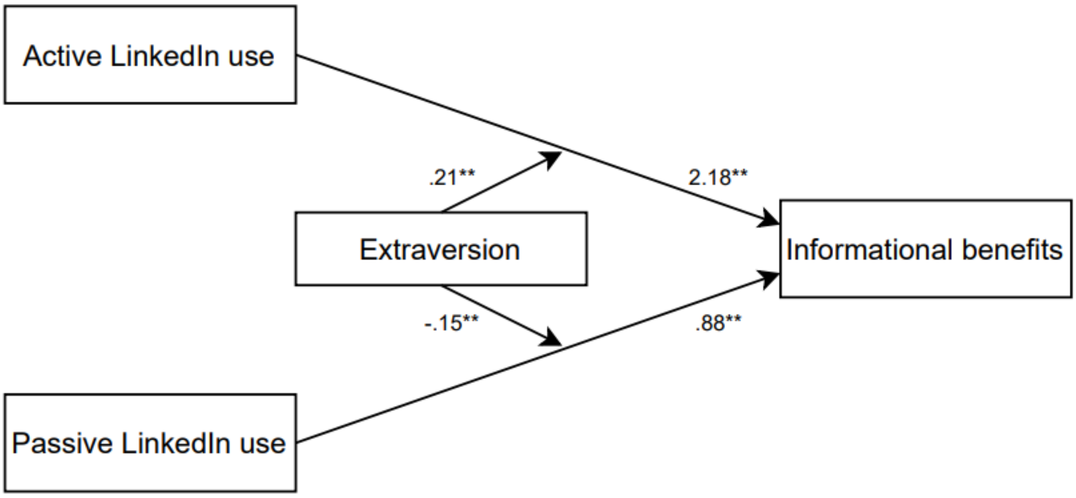
Table C1.

Correlation Coefficients of LinkedIn Variables, LinkedIn Features Use, Extraversion and Informational Benefits. (N=234)

	Informational Benefits
1. Informational benefits	.
2. Extraversion	.115
LinkedIn Variables	
3. Frequency on login	.242**
4. Number of connections	.171**
5. Number of groups	.251**
6. Number of endorsements	.088
7. Number of companies following	.138*
8. Number of influencers following	.026
LinkedIn features use	
9. Forward/share posts published by contacts or other users	.349**
10. Forward/share posts published by companies, influencers, or other groups/channels	.330**
11. Leave likes on posts published by companies, influencers, or other groups/channels	.361**
12. Leave likes on posts published by contacts or other users	.369**
13. Leave comments on posts published by contacts/users	.320**
14. Leave comments on posts published by companies, influencers, or other groups/channels	.358**
15. Follow companies or influencers	.131*
16. Read company/influencer pages	.129*
17. Join groups/channels	.307**
18. Read group pages	.027
19. Update my current status or activities on my homepage	.389**
20. Update or refine my profile	.280**
21. Seek recommendations or endorsements	.300**
22. View others profiles	.303**
23. Add new contacts	.339**
24. Send messages to contacts or other users	.377**

Note. *$p < .05$, **$p < .001$

Appendix D. Conceptual Model with Unstandardized Regression Coefficients and Significance Level



Note: ***p* < .001