

# **Ego Network Analysis: An Overview**

Bachelor's Thesis



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## **Introduction**

Organizations become more and more aware of the fact that they are operating with and within social networks. They are embedded in firm networks, act in target customer networks and are made up of employee networks. Researchers have started to analyze these social networks with respect to their desired outcomes for businesses. One frequently used method is the ego network analysis, which examines social networks from the perspective of a single focal actor. The content and structure of his relations and the relations among his direct contacts can give explanations for the differences in performance of the focal actor and other individuals. In marketing and business related literature, two distinct applications have evolved. Firstly, ego networks are used to examine diffusion and adoption processes of products and secondly, they are analyzed with regard to their influence on employee performance. In the following, the findings of these two literature streams and the way they analyze ego networks are presented and common implications are derived. After a brief overview of ego network analysis components, the biggest part of the work is concerned with reviewing the two literature streams. Thereafter, common findings are summarized and brought together. Finally, the literature is critically evaluated, managerial implications are given and the limitations of this research are presented.

### **Theoretical Background: Definitions and Ego Network Analysis Components**

An ego network is a part of a social network which consists of a focal actor and all of his relations to other people, hereafter called alters, and the relationships among these alters (Wasserman and Faust 1994, p. 42). Burt (1980, p. 80) categorizes ego networks as networks that are, on the one hand, focused on one actor, in contrast to focusing on a specific group or the whole network, and, on the other hand, describe relationships rather than the position of

actors in the whole network. In an ego network analysis these relationships surrounding ego are analyzed with regard to content and structure and the found network properties are then related to outcomes such as ego's performance or well-being. This section consists of a comparison of data collection methods, a review of the major concepts for analyzing content and composition, and a description of the existing structural measures.

### ***Data Collection***

In classical studies, for example Burt's General Social Survey (GSS) (Burt 1984) and Fischer's Northern California Community Study (NCCS) (McCallister and Fischer 1978), the data for the construction of ego networks are obtained by questioning respondents on their social networks. There are usually two types of questions: *Name generators*, asking to whom the respondent maintains a specific type of relationship, and *name interpreters*, asking for information about the alters named and the relationships between these alters (Diaz-Bone 1997, p. 52). The problem with this instrument is that the respondent will only be able to name some alters due to recall issues (Bell, Belli-McQueen and Haider 2007; Matzat and Snijders 2010, p. 105). Thus, the resulting ego networks often do not capture complete personal networks. With the emergence of new technologies and social networking sites (SNS), collecting bigger data became easier. Thus, a lot of recent studies use data obtained from SNS (Brooks et al. 2014; Katona, Zubcsek and Sarvary 2011; Yoganarasimhan 2012) or other means of communication (e.g. call data: Rissealda, Verhoef and Bijmolt 2014 or e-mail data: Aral and Van Alstynne 2011). This enables researchers to construct and analyze much more complete ego networks. Nevertheless, data obtained from SNS like Facebook or Twitter should be used with caution since they might not reflect the 'true' social networks of users, as SNS are often used as a platform for self-portrayal or for "checking out others" (Van den Bulte and Wuyts 2007, p. 5) and not as a means of interaction with the personal network.

### ***Compositional and Content Analysis Components***

In the compositional and content analysis, the resources that ego can draw from are considered. The most obvious measure is *network size*, also often called *degree centrality* (Borgatti and Everett 2006, p. 467), as it can also be a measure of ego's centrality in the whole network. Burt (1983) considers the network size to be an indicator of network range, i.e. the diversity of the ego network: "The number of actors directly connected to an individual is an index of the extent to which the individual is involved in many different relationships" (Burt 1983, p. 177). However, as Diaz-Bone (1997, p. 58) points out, this is only true if the alters are sufficiently different.

This is captured by *heterogeneity or diversity*, which describes the variety of different characteristics of alters. For metrically scaled attributes, the standard deviation is often used (Campbell, Marsden and Hurlbert 1986, p. 105). For nominally scaled attributes, the Gini Index proposed by Corrado Gini in 1912 (Lieberson 1969, p. 851) also referred to as Blau's Index or the  $A_w$ -Index (Lieberson 1969, p. 851), is a good measure of heterogeneity of alters. It assesses the probability that two randomly selected alters are different concerning a specific attribute (Agresti and Agresti 1978, p. 206) and is computed as:

$$\text{Diversity} = 1 - \sum_{i=1}^k p_i^2,$$

Where  $p_i$  is the proportion of alters that correspond to a certain category  $i$  of an attribute of all  $k$  categories of an attribute. A variation of this index is the index of qualitative variation (IQV) by Mueller, Schuessler and Costner (1970, pp. 175-179) which standardizes the value "by dividing [it] by its maximum possible value:  $(k-1)/k$ " (Agresti and Agresti 1978, p. 208).

### ***Structural Analysis Components***

The composition of an ego network is often linked to its structure, which is important for the access to the embedded resources. It is helpful to categorize structural measures into

three categories: measures of ego's position, ego-alter tie attributes and alter-alter tie attributes (cf. Halgin and Borgatti 2012; Park, Lee and Kim 2012).

*Ego's position.* The only meaningful centrality measure to describe ego's position in the ego network is *betweenness* as proposed by Freeman (1982, pp. 293-297) and Everett and Borgatti (2005, p. 32; see also Borgatti, Jones and Everett 1998, p. 31). Betweenness is "the extent to which an actor is between all other actors within the network. If an actor is between two other actors then it follows that there is not a connection between the alters on the path connecting them" (Everett and Borgatti 2005, p. 32). According to Freeman (1982, p. 294) betweenness centrality can be computed as

$$\text{Betweenness centrality of node } i := \sum_{j \neq k \neq i} \frac{g_{jk}(i)}{g_{jk}},$$

where, "the denominator  $g_{jk}$  is the number of shortest paths (geodesics) that connect node  $j$  and node  $k$ , and the numerator  $g_{jk}(i)$  is the number of these geodesics that include node  $i$ " (Bremer et al. 2012, p. 7).

*Ego-alter tie attributes.* Certain types of data collection methods already specify the *type of relationships* between ego and alter, e.g. only formal or informal work relationships (Gonzalez, Claro and Palmatier 2014, p. 76). The relationship type can give hints as to why the network is heterogeneous or homogenous, e.g. family ties and racial homogeneity or age and gender heterogeneity (McPherson, Smith-Lovin and Cook 2001, p. 431). The *multiplexity* of ego-alter ties, meaning that ties consist of multiple types of relationships, e.g. colleagues and friends, can be important to assess the strength of ego-alter ties (Van den Bulte and Wuyts 2007, p. 31). Granovetter (1973, p. 1361) defines the *strength of a tie* as "a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie". Multiplexity can be

measured as the proportion of multiplex relationships in the ego's network:

$$\text{Multiplexity} := \frac{\sum_i z_{ij(m)}}{n},$$

where  $n$  is the number of alters and  $z_{ij}$  is zero if ego  $i$  has only one type of relationship to  $j$  and 1 if the relationship is multiplex (Burt 1980, p. 90). As implied by Granovetter, the time spent interacting also called *channel bandwidth*, as the volume of communication between two actors, also characterizes the strength of the ego-alter tie (Aral and Val Alstynne 2011, p. 119). Another aspect closely related to tie strength is *homophily*, describing the extent to which alter and ego resemble each other (McPherson and Smith-Lovin 1987, p. 370). It should not be confused with homogeneity (described above p. 3) as it does not describe the content of the whole network but is only an aspect of specific ego-alter ties. However, the concepts are often related to each other (McPherson, Smith-Lovin and Cook 2001, p. 424).

*Alter-alter tie attributes.* The by far largest field of analysis with the greatest number of measures is concerned with the overall cohesion of the ego network, i.e. the degree to which alters in the ego network are connected to each other. The first measure is *ego network density*, sometimes also called clustering, which is the proportion of ties present in the ego network to the maximum possible number of ties in the ego network (Wasserman and Faust 1994, p. 101):

$$\text{Density for non directed graphs} := \frac{\sum_{j \neq k} z_{jk}}{n*(n-1)/2},$$

where  $n$  is the number of alters in the ego network and  $z_{jk}$  is equal to 1 if there is a relationship between alters  $j$  and  $k$ .

Another concept measuring the interconnection of alters is *transitivity*. Transitivity exists when two alters that both have ties to a third alter are also connected to each other (Wasserman and Faust 1994, p. 243). Transitivity is often measured as the proportion of three times the existing triangles in the network (excluding ego) to the number of paths of length

two meaning paths in which two alters are connected through a third alter (Brooks et al. 2014, p. 7; Girvan and Newman 2002, p. 7821). Transitivity is a measure of local closure but not necessarily global cohesion as the number of paths of length two decreases if networks are highly clustered into different groups (Brooks et al. 2014, p. 11).

Regarding the extent to which an ego reaches diverse others, one can measure the *structural holes* that ego spans. A structural hole exists if an actor is connected to two other actors that are not connected to each other and are therefore assumed to be different (Burt 1992, p. 18; Van den Bulte and Wuyts 2007, p. 33). The structural holes in an ego network are measured by brokerage or the lack of constraint (Burt 1992, pp. 54-55). Constraint is defined as

$$\text{Constraint} := \sum_j (p_{ij} + \sum_k p_{ik}p_{jk})^2, k \neq i, j,$$

where (in line with Burt 1992, pp. 54-55 and Gonzalez, Claro and Palmatier 2014, p. 83)  $p_{ij}$  captures the proportional strength of the tie, i.e. “the proportion that the tie to  $j$  represents of all ties that [ego] maintains” (Gonzalez, Claro and Palmatier 2014, p. 83).  $\sum_k p_{ik}p_{jk}$  represents the lack of holes around  $j$  with  $p_{ik}$  and  $p_{jk}$  defined in accordance with  $p_{ij}$ . The sum of the two then specifies the effort that ego directly or indirectly (through contact  $k$ ) puts into the relationship with  $j$ . “The expression squared, defines the constraint on [ego] from a lack of primary holes around contact  $j$ ” (Burt 1992, p. 55). This is computed for all  $j$ 's to obtain the total value for constraint. As structural diversity or brokerage is the opposite of constraint, it equals  $1 - \text{constraint}$ .

Another stream of research is concerned with the detection of communities or clusters in social networks (Blondel et al. 2008; Newman 2006). To find communities they optimize modularity, a measure of “the density of links inside communities as compared to links between communities” (Blondel et al. 2008, p. 2).



## **Recent Use of Ego Network Analysis in Marketing and Sociology Literature**

Having its origins in sociology, ego network analysis is increasingly used to analyze the positive outcomes for firms resulting from social networks (Van den Bulte and Wuyts 2007, p. 29). Especially in marketing the concept gained usage in assessing adoption and diffusion processes (e.g. Katona, Zubcsek and Sarvary 2011). Another more inner organizational approach is to analyze the correlation between a manager's success or performance and his social network (e.g. Gonzalez, Claro and Palmatier 2014). This section is concerned with the current marketing literature on product adoption and diffusion and the marketing and sociology literature on manager's performance since these are the most business related topics. It will be shown how ego network analysis is used in this field and which properties of the ego network are related to desirable business outcomes.

### ***Ego Network Analysis in Adoption and Diffusion Processes***

*Adoption of a social networking site - Katona, Zubcsek and Sarvary 2011.* Katona, Zubcsek and Sarvary's study is one of the first relating network properties to adoption processes and thereby analyzing social influences in a more network-based way. They claim that three different effects, network, influencer and adopter effects, affect the likelihood of an individual to log onto an SNS as depicted in Figure 1 [Insert Figure 1 about here]. Firstly, concerning network effects, which describe the ego network of a potential adopter (however, only including already adopted users), size and density are expected to positively influence adoption probability (pp. 429-430). Regarding the influencer, who is a network member of the potential adopter's network, they expect alters' average influential power to decrease with their average total network size, since the strength of ties decreases with the number of friends an actor has (p. 430). As to other influencer and adopter properties such as the betweenness of actors, there are no explicit hypotheses (p. 431) and they only expect an effect.

The ego networks of 138,964 users who registered on a major European SNS during the first 3,5 years of the service (p. 431) were analyzed. They were made up of the ego, being a potential adopter at a time  $t$ , and the later network friends of ego that had already registered at time  $t$  (p. 428). Therefore, the ego networks constructed were only parts of the final friendship networks. The following ego network effects were measured: the proportion of already adopted friends which is a measure of the network size (see above, p. 3), the density (here called clustering coefficient) measured as described above (p. 5) and a degree-clustering interaction term which is made up of the product of the two aforementioned properties (pp. 429-430). The influencer (alter) and adopter (ego) network properties were measured in the final network with 111,036 additional users who registered in the 36 weeks after the observation period (p. 431). This resulting network is assumed to comprise all “real-life friendships” of the egos analyzed (p. 431). Influencer effects include the average number of friends of alters, the average betweenness centrality of alters only considering paths of length two, the average density of alters’ networks and the average age and gender of alters (pp. 430-431). Adopter effects contain the same measures as influencer effects, only calculated for ego, and additionally the population density of the city of residence (p. 431). To relate the ego network measures and the adopter and influencer properties to the probability of adoption in the next period they use discrete-time proportional hazards models (p. 427).

The ego network measures were all significantly positively correlated to the adoption probability across all models and among the three independent variable types the best predictors for adoption (p. 434). The more already adopted friends ego has and the more interconnected they are the more likely it is that he also signs up for the SNS (p. 432). However, also a lot of the influencer and adopter properties were significantly correlated to the adoption probability (pp. 432 and 434). For example, the more friends an influencer has and the denser his surrounding network is, the more likely ego’s adoption (p. 434).

Concerning ego's final network, the more friends he has and the less dense it is in the end, the higher was his adoption probability (p. 434).

The results are limited by the assumption that the final network represents the "real-life" friendship network (p. 431), which is not very likely. Additionally, there is no information about friends that did not eventually register (p. 442). Thus, there is no indication of whether they could have been a negative influence. Moreover, one needs to be careful not to interpret too much into the results as they describe the adoption process of an SNS and not of an actual product.

*Smartphone adoption processes - Risselada, Verhoef and Bijmolt 2014.* In their research, Risselada, Verhoef and Bijmolt use ego networks to test the effects of social influence on smartphone adoption. They examine to what extent the content of the ego network, i.e. if the alters have adopted or not, affects the adoption probability and additionally, if tie strength and homophily further increase the effect (p. 53). Moreover, they expect that these effects vary over time. The underlying hypotheses are: (1) the recent smartphone adoptions in month  $t-1$  in an ego's network (a) unweighted, (b) weighted by tie strength or (c) weighted by homophily positively affect the smartphone adoption probability of ego in month  $t$  (H1, p. 57); (2) the effect of the recent smartphone adoptions (a, b or c) decreases from product introduction onward (H2, p. 57); and (3) the cumulative smartphone adoptions (a, b or c) in the network positively affect the smartphone adoption probability (H3, p. 57). Regarding direct marketing activities they hypothesize that they are positively associated with ego's smartphone adoption probability (H4a, p. 57) and that this effect is constant over time (H4b, p. 57). Figure 2 displays a conceptual model of the hypotheses [Insert Figure 2 about here].

To test these hypotheses they collected a large random sample of customers at a Dutch mobile telecommunications operator and constructed 15,700 ego networks out of the call

detail records of the company (pp. 57-58). Alters were all contacts ego called or texted. The dependent variable, the time of adoption, was measured as “the number of months between the telecommunications operator’s introduction of the smartphone [...] and a customer’s adoption of the product” (p. 57). The social influence variables were collected as the number of alters that bought a smartphone in month t-1 (recent adoptions) and the cumulative number of smartphone purchases among alters up to and including t-2 (p. 58). Strength of the tie was measured as the frequency of interaction, i.e. the ratio of calls and texts to and from a certain alter to the total calls and texts of ego (p. 58). Homophily is measured as the similarity of ego and alter on sociodemographic variables (age, gender, education level, and income), where similarity on an attribute adds .25 to the similarity measure (age is similar if the difference is less than or equal to five years) (p. 58). The direct marketing effort is measured as the direct marketing actions (e-mail, text message, or bill supplement) a customer received (p. 58). As the aforementioned research, they used a fractional polynomial hazard approach (p. 59).

Risselada, Verhoef and Bijmolt found that recent adoptions weighted by tie strength are significantly and positively correlated to the likelihood of adoption of ego (p. 61) and that this effect is constant over time (support for H1b). Additionally, the cumulative number of adoptions positively and significantly affects the adoption probability and this effect decreases over time (support for H3a) (p. 61). If the cumulative number of adoption is weighted by the similarity of ego and alters, it is also significantly and positively correlated and the effect stays constant over time (support for H3c) (p. 62). As later simulations show (pp. 62-63), the weighted variables significantly improve model fit, even though they are only significant for certain social influences. Direct marketing also affects adoption probability positively and significantly but the effect decreases over time (support H4a but not H4b) (p. 62). As both direct marketing and social influence variables have an impact, one can conclude that direct marketing does not take away the effect of social influence.

Limitations of these findings are that they might not accurately capture smartphone adoptions, since they did not have any information about customers that left the phone company. These might have purchased a smartphone at a different company (p. 64). On top of that, it is not clear whether the researchers had the information on the phone types of alters who did not have a contract with this phone company.

*Diffusion of YouTube videos – Yoganarasimhan 2012.* In contrast to the publications above, Yoganarasimhan's study is apparently the first empirical research about the correlation between the ego network structure and the diffusion of the ego's products (p. 115). It examines how characteristics of the YouTube network around a video author affect the diffusion and success of his videos. Even though the study examines the 2-degree network of a video author including the alters' friends (pp. 121-122), it can be considered as a study of the ego network as it analyzes the structure of a focal actor's relationships. Yoganarasimhan expects an influence of network size, density and betweenness on video performance (p. 112).

The author randomly collected publicly available YouTube video data and network data of the corresponding authors (p. 117). The collected data on the videos include the views, number of ratings, average rating, comments, favorited and honors. The compositional network measures comprise the author's degree, the amount of second-degree friends and the average friends of first-degree friends. The alter-alter ties are being analyzed through density. And ego's position is measured by the normalized-2-betweenness calculated as above (p. 4) but including not only paths of length up to two but four since the alters' friends are included (pp. 122-124). Yoganarasimhan models the video popularity, i.e. the number of views received in a specific period, as being dependent on the views the video received in the past periods, the video characteristics of the last period and the ego network properties. These video characteristics are time varying whereas the social network properties are time invariant and stable measures (p. 126). An illustration of the model can be found in Figure 3 [Insert

Figure 3 about here].

Yoganarasimhan finds that the personal network size is positively correlated to video success (p. 134). By taking a closer look, it seems that more friends of alters (second degree) is more important than more alters (first degree) (p. 135). A possible explanation would be that “even though first-degree friends have better access to and greater interest in an author’s video, second-degree friends have larger and wider networks” (p. 135). In a later model comparing the effect of early versus later video viewership the author finds that first degree friends are important in earlier stages, whereas second degree friends’ importance increases in later stages (p. 141). Contrary to Katona, Zubcsek and Sarvary’s (2011) findings, high density is negatively correlated to video popularity (p. 136). This difference can be explained as the former looked at adoption, whereas this research focuses on diffusion. Members of a dense community might be more likely to adopt or, in this case, view the video. However, they “may not interact much with outsiders even if they are connected to them, thereby failing to spread information about the video to the wider network” (p. 136) which is also in line with Granovetter’s (1973) strength of weak ties theory. The third network characteristic betweenness centrality is also negatively correlated to the diffusion of videos (p. 136). This is also surprising as betweenness is usually assumed to be beneficial to ego’s social capital (Borgatti, Jones and Everett 1998, p. 31) because a higher betweenness implies that ego has a dominant position in the network and connects others (p. 137). In this setting however, the negative effect of betweenness, the lower path diversity, i.e. the low number of different paths ego has to reach the outer network, might be stronger, leading to a negative influence of betweenness on diffusion. As the author describes later, density and betweenness only significantly impact popularity in later stages of the diffusion process (p. 141). Other findings are that viewership is significantly correlated to viewership from the last two days and other video characteristics (pp. 137-138).

### ***Ego Network's Relation to Managerial Performance***

*Relationship manager's performance – Gonzalez, Claro and Palmatier 2014.* In most studies ego networks are not used to test the success or diffusion of a product but to assess the social networks in terms of their positive outcomes for individuals. In their research Gonzalez, Claro and Palmatier (2014) “develop and test a model that links objective sales performance with the informational and cooperative benefits that stem from relationship managers' (RMs') social capital structure (brokerage and density) and relations (formal and informal networks)” (p. 76), where RMs are “boundary-spanning employees who occupy a central role in relationship marketing implementation and are responsible for end-to-end relationships with customers” (p. 76).

Their research is based on social capital theory claiming that there are two kinds of positive outcomes in social networks leading to better performance: information benefits stemming from structural holes in the ego network (Burt 1992, pp. 13-17) and cooperative support resulting from very dense personal networks (Coleman 1988, pp. S105-S107). Consequently, the authors expect that structural holes (brokerage) and density positively affect RM performance ( $H_1$  and  $H_2$ ) (pp. 80-81). Moreover, the authors suspect synergies between the formal and informal networks that can be found in a firm (p. 76). With regard to cross-network synergy, meaning that ego will benefit from diverse information in one network and cooperative support in the other (p. 77), they postulate that the positive effect of brokerage in the informal (formal) network on RM performance is enhanced as density increases in the formal (informal) network ( $H_3$  and  $H_4$ ) (p. 81). The fifth and sixth hypotheses concern overlap-network synergy, which basically describes multiplex relationships (see above, pp. 4-5) between RMs (p. 79). They assume that the positive effect of brokerage and respectively density in formal and informal networks on RM performance increases as multiplexity increases (pp. 81-82). An overview of the conceptual model is shown in Figure 4

[Insert Figure 4 about here].

To test their model, Gonzalez, Claro and Palmatier examined the formal and informal networks of 101 RMs in a B2B firm and related them to their sales growth (pp. 82-83). The formal network was constructed out of the firm's organizational charts (p. 82) and the informal network was obtained by asking employees the name generator questions: "Whom would you trust to confide your concerns about work-related issues, and whom would you invite to happy hour after a workday?" (p. 82). Even though, they were able to construct the complete firm network, they only used the RM's ego networks for the analyses. Brokerage, density and multiplexity are measured as explained above (p. 83). They used ordinary least squares regressions to test the main effects. To evaluate the effects of network synergies the corresponding measures were included as moderating effects (pp. 85-86).

Regarding the main effects ( $H_1$  and  $H_2$ ), only brokerage and density in the RM's formal network are significantly positively correlated to his performance (p. 86). In the mediated model including network synergies only brokerage in formal networks is significant (p. 86). As there is no significant correlation for informal networks, Gonzalez, Claro and Palmatier reason that "simply befriending people in the firm offers little direct benefits" (p. 86). Only when looking at the moderating effects of network synergies, informal networks become important. Having an informal network with more structural holes and simultaneously a dense formal network increases performance due to the cross-network synergy hypothesized in  $H_3$  (p. 87). Vice versa ( $H_4$ ), no positive impact (p. 87) can be found. Looking at overlap-network synergies, the positive effects of formal and informal network brokerage ( $H_5$ ) and informal network density ( $H_{6b}$ ) are enhanced when multiplexity increases. For overlap-network synergy in dense formal networks ( $H_{6a}$ ) no significant relationship to performance can be found (p. 87). These findings are limited to the extent that the authors only looked at one specific firm and it might be different for other firms (p. 92).



*Benefits of structural holes – Rodan 2010.* Unlike the preceding study, Rodan only expects an effect of structural holes on managerial performance. By obtaining ego networks he tries to discover the mechanism through which structural holes lead to better performance.

The research is based on Burt's (1992) structural holes theory and an earlier research by Rodan and Galunic (2004), who suggest that the performance benefits from structural holes stem from network structure, i.e. the extent to which alters are connected, and from network content, i.e. the alters' knowledge heterogeneity. Rodan assumes that this relation is potentially caused by five different mechanisms: autonomy, opportunity recognition, competition, information arbitrage and innovativeness (pp. 168-169). To test which one is the responsible, he forms five hypotheses: The responsible mechanism is

- ... autonomy, if the network structure is the only significant correlate, as ego can act freely if his contacts are not interacting to control his actions.
- ... opportunity recognition, if knowledge heterogeneity is the only significant correlate, because opportunities arise as ego gets diverse information.
- ... competition, if knowledge homogeneity and network structure are both strongly correlated, since only substitutable, disconnected alters compete for ego's attention.
- ... information arbitrage, if, in contrast, knowledge heterogeneity and network structure are both significantly correlated, as information arbitrage arises when ego is the only connection between two heterogeneous alters.
- ... innovativeness, if innovativeness strongly mediates the influence of knowledge heterogeneity and network structure on performance (pp. 169-171).

(For an overview of the hypotheses see Figure 5) [Insert Figure 5 about here]

Ego networks of managers at a Scandinavian telecommunications company (p. 171) were collected in interviews using name generator and name interpreter questions (pp. 171-172). Managers were not only asked about the tie strength but also about the knowledge

heterogeneity in their network. As in Gonzalez, Claro and Palmatier (2014), nearly complete firm networks were obtained but later on, only ego network measures are computed (p. 173). The author questioned two senior managers on the performance and innovativeness of the respondents (pp. 173-174). Density instead of constraint is used to measure the extent to which the network structure consists of disconnected alters since constraint “embodies some assumptions about mechanisms” (p. 173). To compute alter knowledge heterogeneity, a measure developed by Rodan and Galunic (2004, pp. 549-550) is used which increases as network size or knowledge distance between ego and alters or between alters increases.

Rodan uses six different regression models to sequentially test the hypotheses. The first one verifies that ego-network density is in fact negatively correlated to job performance (p. 175). Second, he finds that there is also a significant negative relationship between knowledge heterogeneity and ego-network density (p. 176). After testing the potential mediating effect of knowledge heterogeneity on the density-performance relationship, it turns out that knowledge heterogeneity does not fully mediate it (p. 176). Since neither density nor knowledge heterogeneity alone is responsible for performance, the autonomy and opportunity recognition hypotheses can be rejected. To test arbitrage and competition as responsible mechanisms, a density-knowledge heterogeneity interaction term is added (p. 176). In that case, knowledge heterogeneity is significantly positively and the interaction significantly negatively correlated to performance (p. 176). This is consistent with the hypothesis about information arbitrage as there is a positive effect of knowledge heterogeneity. Consequently, the competition hypothesis can be rejected (p. 170). The last two models test the potential mediating relationship of innovativeness. First, it is shown that innovativeness is correlated to density, knowledge heterogeneity and the interaction term. When innovativeness is included as a mediator in the regression model, it is the only factor significantly increasing job performance. Therefore, one can assume that innovativeness and not information arbitrage is

the mechanism responsible for connecting structure, i.e. density, and knowledge heterogeneity to managerial performance (p. 176). As in the previous publication, the data were obtained in only one company and the results are therefore limited (p. 176). Considering that managerial innovativeness and performance were rated by the same senior managers, “the greater the extent to which these senior managers saw innovativeness as synonymous with performance, the more closely the two outcome measures would be correlated which could artificially inflate the mediating effect of innovativeness” (p. 176). Additionally, the results were obtained in a Scandinavian company and their culture is assumed to be less driven by competitiveness (Hofstede 1980, p. 54) which might further influence the findings (p. 176).

*Diversity-bandwidth trade-off – Aral and Van Alstyne 2011.* This article also examines structural holes in ego networks focusing on the information benefits that they bring and how these are related to employee performance. Structural holes theory (Burt 1992, pp. 13-17) and strength of weak ties theory (Granovetter 1973, pp. 1370-1378) suggest that more novel information flows through weak, disconnected ties of the ego network and that more novel and diverse information is associated with positive outcomes (p. 92). However, as the authors claim, weak ties are associated with less frequent interactions between ego and alter. Thus, novel information could actually reach ego later than information from his strong tie contacts who are assumed to communicate more often and give more detailed and relevant information due to more motivation and trust (p. 94). As follows, the authors suspect both network diversity, i.e. structural holes, (H1a) and channel bandwidth (H1c), i.e. the frequency of interaction between ego and alter, to be positively related to information diversity and the total non-redundant information received over a certain time span. In accordance with strength of weak ties theory, they hypothesize that “network diversity is associated with lower channel bandwidth” (H1b, pp. 109 and 91-101). On top of that, they make several hypotheses about the information environment. The authors hypothesize that the more information or

topics alters share (information overlap), the less important structural holes are (H2a, pp. 104-105). Additionally, the more information about different topics alters have (topic space) and the more often topics about which the alters have information change (information refresh rate), the more valuable the frequency with which alter and ego interact. (H2b and H2c, pp. 105-108). Regarding performance, they hypothesize that “access to non-redundant and diverse information is positively associated with individual performance” (H3, p. 109). (For an overview of the interdependencies see Figure 6) [Insert Figure 6 about here]

The hypotheses are tested using ego networks constructed from the e-mail communication at an executive recruiting firm in the US, where a tie is an e-mail between a recruiter and one of his contacts. Network diversity is measured using the structural holes measure constraint (see above p. 6). Additionally, structural equivalence, i.e. the extent to which alters in the network occupy the same positions, is assessed using the Euclidean distance (p. 119). Average channel bandwidth is measured as the average amount of incoming e-mails from one contact over the total number of contacts at time  $t$  (p. 119). To obtain a measure for information diversity and total non-redundant information, the e-mail content is analyzed using a vector space model of communication content (p. 119-127), which compares the diversity of topics discussed in e-mails. Performance is measured as completed projects, generated revenues and average project duration (pp. 116-117).

Their first two models estimate bandwidth and network diversity as functions of the other and further control variables (p. 160). These models give evidence for the diversity-bandwidth trade-off as channel bandwidth is negatively correlated to network diversity and positively correlated to structural equivalence (p. 132). Subsequently, the authors modeled information diversity (ID) and the total non-redundant information (NRI) as being dependent on network diversity, structural equivalence, bandwidth and other control variables, e.g. the total number of incoming e-mails (p. 163). Results were that both network diversity and

channel bandwidth positively affect ID but network diversity has a greater effect (1-SD increase in channel bandwidth led to 0.085-SD increase in ID, whereas 1-SD increase in network diversity increased ID by 0.15 SD) (pp. 138-139). On the other hand, they found that channel bandwidth has a greater effect on NRI (1-SD increase in channel bandwidth led to 0.35-SD increase in NRI, whereas 1-SD increase in network diversity only increased NRI by 0.07 SD) (p. 142). Regarding the environment hypotheses (H2a-c), they found prove for all of them (p. 143). Finally, performance was modeled as a function of bandwidth, network diversity, ID and NRI (p. 163). Network diversity is stronger correlated to performance than bandwidth and remains significant even when the measure for NRI and ID are added to the model, implying that “benefits of network diversity come not just from the access to novel information but also from other mechanisms such as better job support, more power or organizational influence” (p. 146). The results are limited by the fact that they were produced in only one firm in the United States and the authors only looked at e-mail ego networks.

### **Conceptual Framework**

There are two main results from the comparison of the articles in the two literature streams: firstly, it becomes clear that the compositional and structural network measures are often highly interlinked and secondly, there is no clear indication if structural holes or density are more desirable. This always depends on the outcome analyzed and the environment.

Concerning the first finding, several prior works also claimed that the network measures are associated to one another. Dense networks are often characterized as being homogeneous and made up of strong ties (Granovetter 1973, p. 1370; Marsden 1987, pp. 128-130), whereas sparse networks full of structural holes are considered to be heterogeneous and to be consisting of weak ties (Burt 1992, pp. 25-30).

This is also shown in the literature on ego's job performance. In Rodan (2010), one of the results is that density is negatively correlated to knowledge heterogeneity (p. 175) suggesting that dense networks are homogenous whereas sparse networks are heterogeneous. In Gonzalez, Claro and Palmatier (2014), the correlation matrix (p. 84) shows that network overlap, i.e. multiplexity, is strongly positively linked to density and strongly negatively linked to brokerage, i.e. structural holes in both formal and informal networks. If multiplexity is associated with tie strength (see above pp. 4-5), dense ego networks are made up of stronger ties than ego networks with structural holes. This relationship is also shown in Aral and Van Alstynne (2011), as network diversity, i.e. the lack of constraint, is strongly negatively linked to channel bandwidth (p. 134), i.e. the frequency of interaction between ego and alter, which is supposed to be a good indicator of tie strength (see above pp. 4-5).

In the literature on adoption and diffusion processes, the links between the network measures are not found that easily. However, considering that Katona, Zubcsek and Sarvary (2011) and Risselada, Verhoef and Bijmolt (2014) both examine adoption processes, their results can be compared (even though with some caution since the two adoption products, SNS and smartphones, are quite different). The former assess structural alter-alter tie measures (density), the composition of the network (number of already adopted alters) and the position of influencers and adopters in the network (betweenness centrality). The latter are more concerned with the content of the network as measured with the smartphone adoptions in the ego network and the properties of ego-alter ties such as the tie strength or homophily. In both studies the number of adoptions in the network (Risselada, Verhoef and Bijmolt 2014, pp. 61-62) respectively the number of alters that have already adopted (degree in Katona, Zubcsek and Sarvary 2011, p. 432) increases the likelihood of adoption. Additionally, in both the result is enhanced if the network is dense, respectively, if the ego-alter ties are strong and characterized by homophily. Thus, since density and strong ties both increase the likelihood

of adoption, one could infer that these are often found in the same networks.

With regard to the second finding, the literature on adoption and diffusion processes shows that the most useful structure depends on the outcome analyzed. Adoption probability was increased if influencers and adopters had dense networks (Katona, Zubcsek and Sarvary 2011, p. 432). In the case of diffusion, density was detrimental to video viewership and thus to diffusion (Yoganarasimhan 2012, p. 136). In adoption processes, the positive effect of being closer to alters and thereby being more influential is likely to be more important. This can also be inferred from the positive effect of tie strength in Risselada, Verhoef and Bijmolt (2014, p. 63). On the other hand, in diffusion processes, density is likely to have a negative effect as it impedes ego from reaching diverse others (Yoganarasimhan 2012, p. 136). Therefore, density can be assumed to be beneficial if adoption is examined whereas in diffusion processes it is likely to be harmful.

Concerning job performance, there are no clear indications whether density or structural holes are more desirable and it most likely depends on the firm environment and the way the ego networks are constructed. In Gonzalez, Claro and Palmatier's (2014) study, density and structural holes in formal networks both significantly positively influence relationship manager's performance (p. 86). They suggest having dense formal networks while simultaneously maintaining structural holes in informal firm networks to benefit from both the cooperation and trust in dense networks and the information diversity in networks with structural holes. However, this might only be true for that specific firm because in other firms formal and informal networks might look different. The other articles did not differentiate between different types of relations. In Aral and Van Alstynne's (2011) study of firm e-mail networks, more structural holes led to better performance (p. 145). At the same time bandwidth, i.e. the frequency of interaction, also indirectly influences performance as it is positively correlated to the total non-redundant information ego receives. Bandwidth is

associated with tie strength (p. 93; Granovetter 1973, p. 1370) and, as mentioned above, tie strength is linked to density. Thus, also in this research, structural holes and density both bring benefits even though the effect on performance seems to be greater for structural holes. In contrast, Rodan (2010) finds that, in his study, density is significantly negatively correlated to performance (p. 175). Thus, he concludes that only structural holes are beneficial. Since the results are in all cases slightly different, it is likely that the respective benefit of structural holes and density depends on the firm environment and the way in which one analyzes the ego network structure, i.e. formal and informal networks, e-mail networks, interviews asking for contacts with different types of relationships. If in the firm environment density leads to more communication on relevant business topics, as suggested by Aral and Van Alstyne, (2011), and one can suspect that this also happens in the formal networks analyzed by Gonzalez, Claro and Palmatier (2014), this leads to more total non-redundant information and therefore better performance. If otherwise network density only causes individuals to discuss redundant and irrelevant topics, as it could be the case for the informal networks analyzed by Gonzalez, Claro and Palmatier (2014), in which density had a slightly negative but insignificant effect on performance (p. 86), ego network density is harmful to job performance as suspected by Rodan (2010).

## **Discussion**

### ***Critical Evaluation***

As explained above, the results are often dependent on the situation and the environment in which the ego networks are set. Therefore, one has to be careful not to infer too much from the results. For example, in the case of job performance in relation to personal networks, job performance is often influenced by the firm's culture and how they evaluate



performance. Additionally, for the adoption and diffusion processes, the results should not be regarded as true for all types of products. Taking for example Yoganarasimhan's (2012) research, density negatively influenced the diffusion of YouTube videos. The videos are most likely low involvement products (cf. Homburg and Krohmer 2009, p. 39) as there are no particular risks associated with watching them. Thus, alter-ego trust is not needed to influence others to watch a video. Regarding high involvement products, trust and therefore strong ties and density might be more valuable as in the Smartphone adoption case of Risselada, Verhoef and Bijmolt (2014). Signing up for an SNS (Katona, Zubcsek and Sarvary 2011) might also entail more involvement as one exposes oneself and thus has more risks.

Furthermore, the ego networks that were collected might be biased. For example, in Risselada, Verhoef and Bijmolt (2014), the smartphone purchases in the personal network can only be assessed if the alters are customers of the Dutch telecommunications company from which the data was obtained. In Katona, Zubcsek and Sarvary (2011), the ego networks only consist of alters that eventually signed up for the SNS. And, in Aral and Van Alstynne (2011), the e-mail ego networks might also not capture the exact personal networks in the firm, since they only represent one means of communication.

Regarding the use of ego networks in general, as shown in Yoganarasimhan's (2012) findings, the rest of the network might also be very influential. However, their influence cannot be analyzed in ego networks.

### ***Managerial Implications***

There are three types of implications for managers, one for each type of outcome reviewed and one for using ego network analysis in general. Concerning the diffusion of products, if firms want to seed content related to their products in an SNS, they should look for networks rich of structural holes to reach into diverse parts of the whole network (Yoganarasimhan 2012). To create high adoption of products, firms should look for inno-

vators and early adopters with dense networks of imitators as they very likely influence their contacts to adopt (Katona, Zubcsek and Sarvary 2011; Risselada, Verhoef and Bijmolt 2014).

Regarding managerial performance, firms should encourage managers to build personal networks that reach out to diverse others but also have a tight core of employees surrounding them in their everyday work. Thus, they can benefit from structural holes and their diverse information and strong ties and the trust, cooperation and frequent interaction that comes with them as proposed by Gonzalez, Claro and Palmatier (2014, p. 91).

Lastly, some implications for the usage of ego networks are that the outcomes and the environment should be clearly analyzed and defined. The extent to which the ego network measures are beneficial depends on the situation, for example, density is better when looking for trust and cooperation (Coleman 1988, pp. S105-S107), whereas structural holes are more important when looking for diversity (Aral and Van Alstynne 2011, p. 138).

### ***Limitations and Future Research***

This was only a short overview of how ego network analysis can be used for marketing and business related purposes. There are a lot of other applications of ego network analysis, especially in the field of sociology, for example in the evaluation of SNS (Brooks et al. 2011, 2014; Ellison, Steinfield and Lampe 2007; Williams 2006), in analyzing core discussion networks (Brashears 2011) or in assessing how residential mobility changes social support networks (Viry 2012). Therefore, this overview is by no means exhaustive.

Also, some assumptions, e.g. that density and the existence of structural holes are mutually exclusive, might be false in particular situations. Some of these long-held assumptions have already been proven to not always be true. For example, Granovetter (1973, p. 1363) argued that if two people are strongly tied to a third one, there is always an at least weak tie between these two people, i.e. transitivity. However, Mollenhorst, Völker and Flap's (2011) research shows that this theorem is not always true as those unclosed triangles occurred

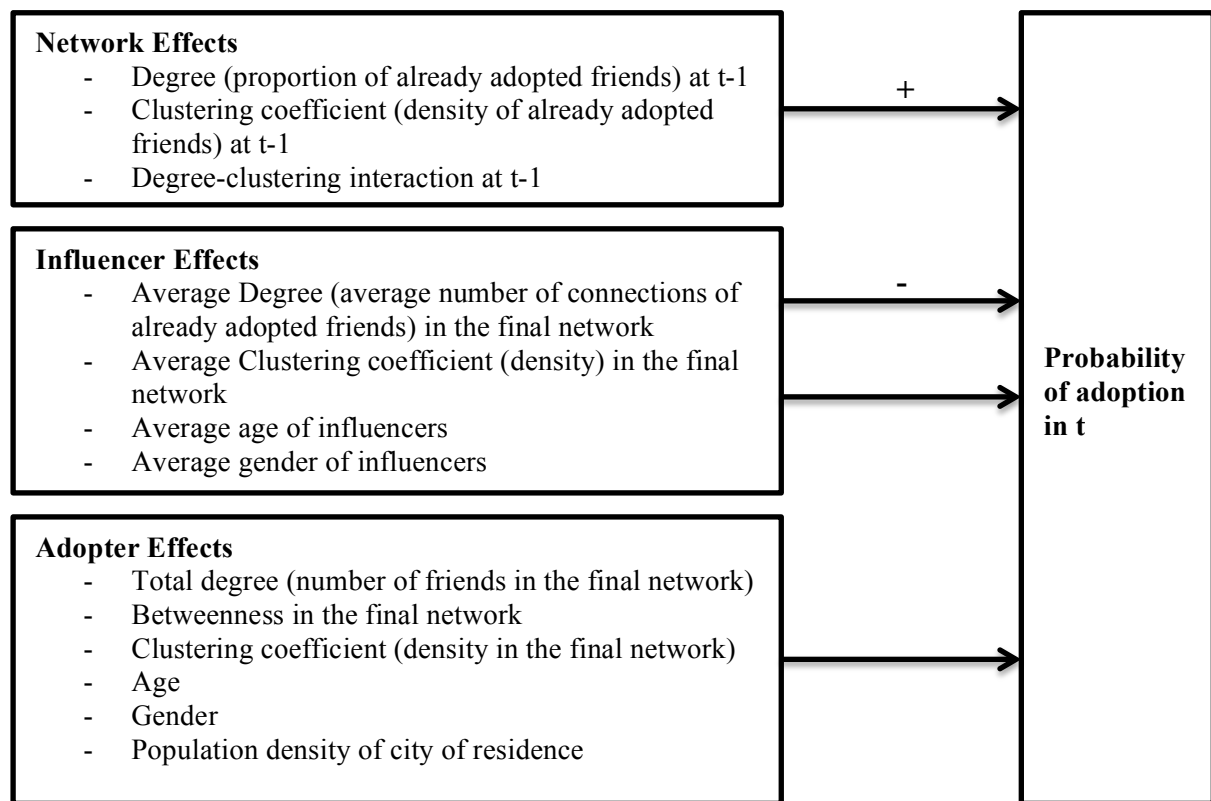
quite often in their data (p. 300). Therefore, the assumptions made should be closely reviewed and the relationship between dense networks and the absence of structural holes should be examined further. Is it really not possible to have a dense personal network also inheriting structural holes and to benefit from both of them?

Besides, more attention should be paid to the analysis of ego network betweenness. Betweenness centrality is usually assumed to be beneficial to ego as it is associated with a dominant position in the network (Borgatti, Jones and Everett 1998, p. 31; Freeman 1979, p. 224). However, in the studies that included ego's position as a structural measure (Katona, Zubcsek and Sarvary 2011, p. 434; Yoganarasimhan 2012, p. 136), ego network betweenness was negatively correlated to adoption and diffusion respectively.

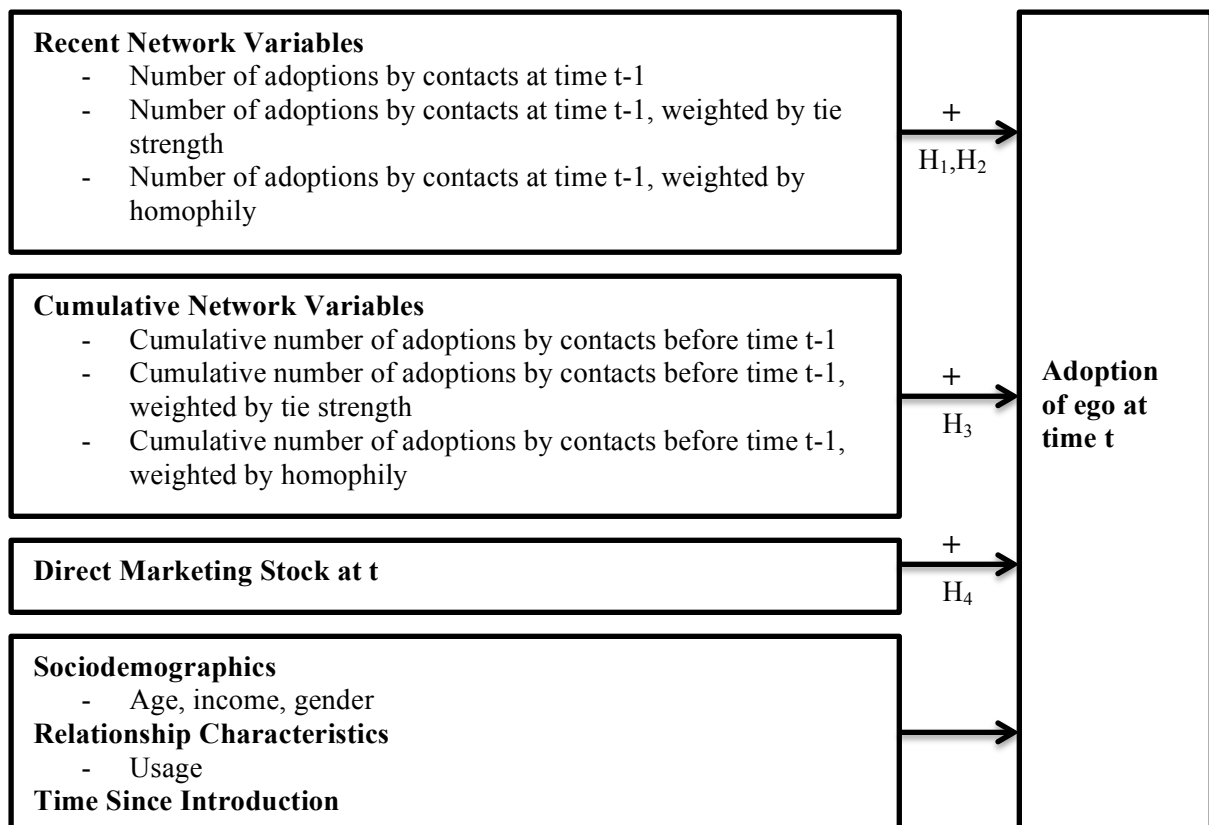
This overview has shown that there are applications for ego network analysis in marketing. However, this tool has not yet been exploited to the fullest, which is also claimed by Yoganarasimhan (2012, p. 117). There should be more research on how the personal network of diffusers can influence product success and if this is dependent on the type of products (high vs. low involvement). Moreover, ego network analysis in online social networks could detect beneficial online strategies for firms who begin to have profiles on SNS such as Facebook, Twitter and Co.

## Figures

*Figure 1: Conceptual Model - Katona, Zubcsek and Sarvary 2011*

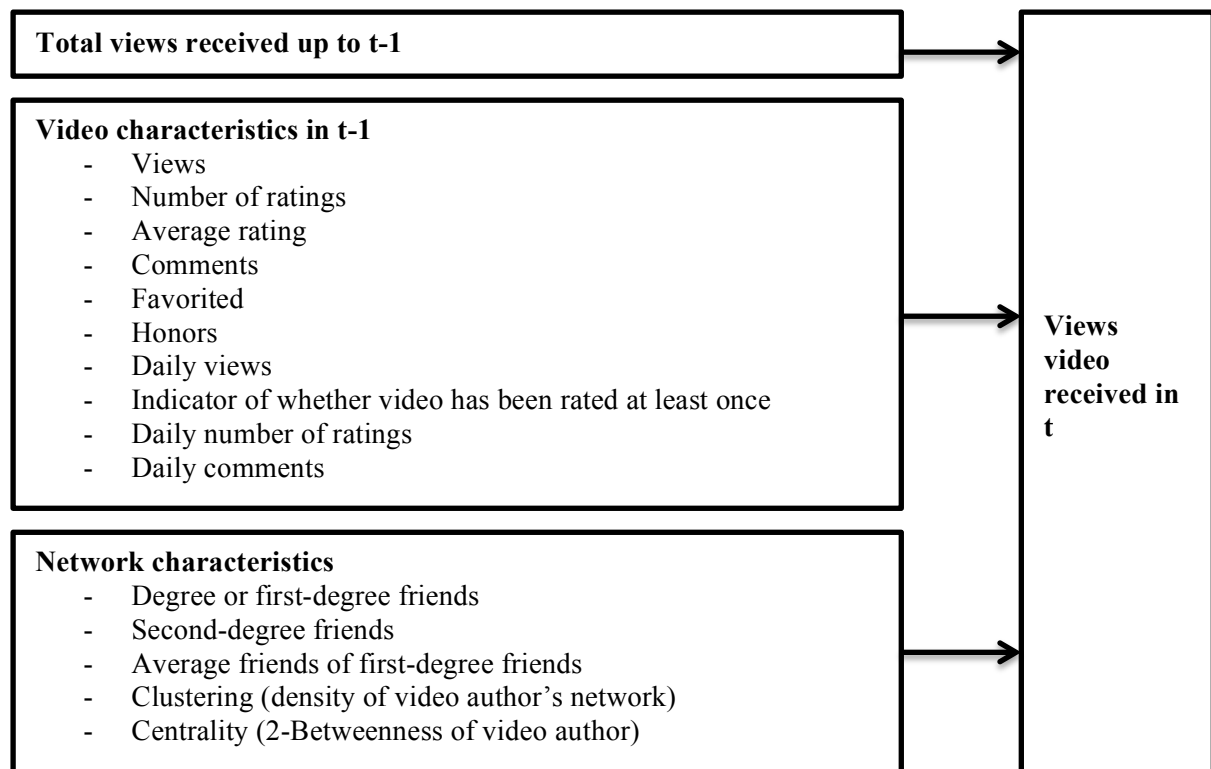


**Figure 2: Conceptual Model - Risselada, Verhoef and Bijmolt 2014**

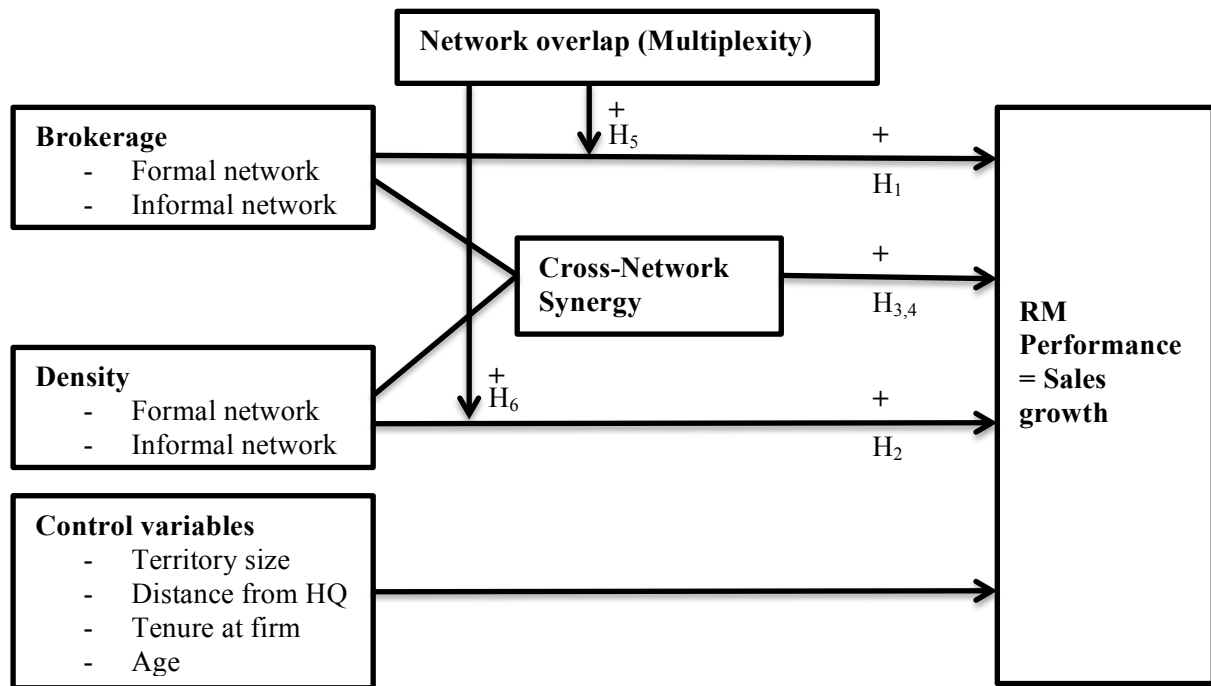


(see Risselada, Verhoef and Bijmolt 2014, p. 56; reworked by the author)

*Figure 3: Conceptual Model - Yoganarasimhan 2012*

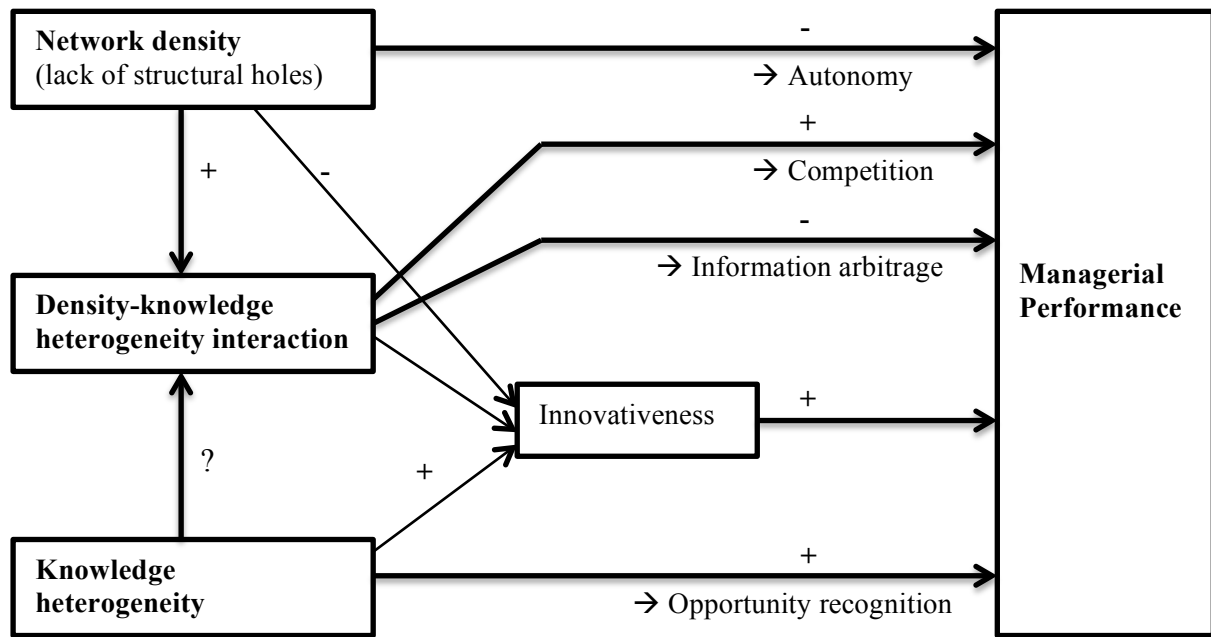


*Figure 4: Conceptual Model - Gonzalez, Claro and Palmatier 2014*



(see Gonzalez, Claro and Palmatier 2014, p. 80; reworked by the author)

*Figure 5: Conceptual Model - Rodan 2010*

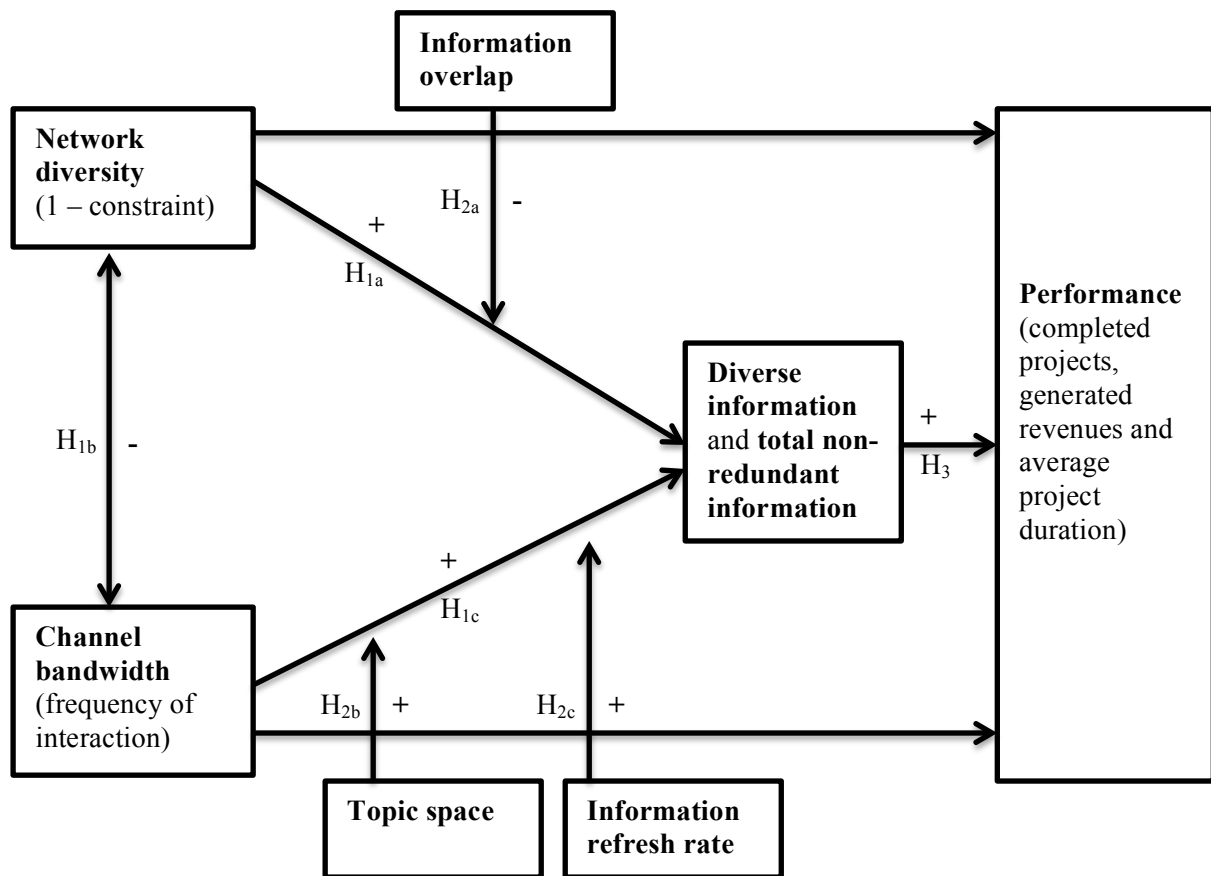


**Control Variables:** tenure, level of education, gender, seniority, departmental affiliation, network size

(see Rodan 2010, p. 169; reworked by the author)



*Figure 6: Conceptual Model - Aral and Van Alstyne 2011*



**Control variables:** expertise heterogeneity of alters, demography, human capital, total communication volume, individual characteristics and temporal shocks

**List of Abbreviations**

B2B	Business-to-business
ID	Information diversity
NRI	Total non-redundant information
RM	Relationship manager
SD	Standard deviation
SNS	Social networking site

## Literature Review Tables

Author/s (Year) [Journal]	Research Focus	Theoretical Background	Outcome Analyzed	Sample	Method/ Analysis	Independent Variables	Main Findings
Katona, Zubcsek and Sarvary (2011) [Journal of Marketing Research]	Effect of the ego network structure, attributes of already adopted alters and ego on ego's adoption	<ul style="list-style-type: none"> <li>- Marketing literature on product diffusion, e.g. Bass (1969) model</li> <li>- Sociology literature on social network analysis, e.g. network closure theory (Burt 2005; Coleman 1988)</li> </ul>	Probability of adoption of a major European social networking site (SNS)	n = 250,000 users Data on networks, registration time and demographics obtained from the SNS over a period of 1247 days (no information on the year)	Continuous-time proportional hazards model	<p><i>Network effect measures</i></p> <ul style="list-style-type: none"> <li>- Proportion of already adopted friends, i.e. network size at time t to total network size at the end</li> <li>- Density of already adopted friends at time t</li> <li>- Interaction between network size and density</li> </ul> <p><i>Influencer measures</i></p> <ul style="list-style-type: none"> <li>- Average total number of friends</li> <li>- Average betweenness</li> <li>- Average density</li> <li>- Average age and gender</li> </ul> <p><i>Adopter measures</i></p> <ul style="list-style-type: none"> <li>- Total number of friends in the final network</li> <li>- Betewenness in the final network</li> <li>- Density in the final network</li> <li>- Age, gender and population density of the city of residence</li> </ul>	<ul style="list-style-type: none"> <li>- Individual who is connected to many adopters has a greater adoption probability</li> <li>- Density in the ego network consisting of already adopted friends has a strong positive effect on the adoption of ego</li> <li>- Demographics and network position of influencers and adopters are good predictors of adoption</li> </ul>

Author/s (Year) [Journal]	Research Focus	Theoretical Background	Outcome Analyzed	Sample	Method/ Analysis	Independent Variables	Main Findings
Risselada, Verhoef and Bijmolt (2014) [Journal of Marketing]	Dynamic effects of social influence and direct marketing on smartphone adoption	<ul style="list-style-type: none"> <li>- Marketing literature on product diffusion, e.g. Bass (1969) model</li> <li>- Sociology literature on social network analysis</li> </ul>	Time of adoption as the number of months between the telecom- munications operator's introduction of the smartphone and the adoption	n = 15,700 customers of a Dutch mobile telecom- munications operator Call, marketing and smartphone purchase data collected during April 2007 and September 2009	Fractional polynomial hazard model	<p><i>Social influence</i></p> <ul style="list-style-type: none"> <li>- Number of contacts that adopted in month t-1, unweighted, weighted by tie strength and weighted by homophily</li> <li>- Cumulative number of adoptions among a customer's contacts up to and including t-2, unweighted, weighted by tie strength and weighted by homophily</li> </ul> <p><i>Direct Marketing</i></p> <ul style="list-style-type: none"> <li>- Number of direct marketing actions a customer received up to t</li> </ul>	<ul style="list-style-type: none"> <li>- Effect of cumulative adoptions in a customer's network is positive but decreases from the product introduction onward</li> <li>- Effect of recent adoptions is positive and remains constant</li> <li>- Effect of direct marketing is positive and decreases from the product introduction onward</li> <li>- Including homophily and tie strength significantly increases model fit</li> </ul>

Author/s (Year) [Journal]	Research Focus	Theoretical Background	Outcome Analyzed	Sample	Method/ Analysis	Independent Variables	Main Findings
Yoganarasimhan (2012) [Quantitative Marketing and Economics]	Effect of the local network around a node on the diffusion of its products	<ul style="list-style-type: none"> <li>- Literature on peer-effects</li> <li>- Literature on opinion leaders</li> </ul>	Popularity of a YouTube video measured as its views	<p>n = 1806 authors of YouTube videos</p> <p>Randomly selected 1939 videos on YouTube in November 2007 and obtained video data for 38 days and network data on 1806 corresponding authors who had publicly listed their friends</p>	Linear regression model and dynamic panel data estimator to handle the endogeneity problems	<p><i>Video characteristics of the past period</i></p> <ul style="list-style-type: none"> <li>- Daily Views, daily number of ratings, indicator variable for no rating, average rating, daily comments, favored, honors</li> </ul> <p><i>Social network properties</i></p> <ul style="list-style-type: none"> <li>- Number of first-degree friends, second-degree friends and total</li> <li>- Avg. friends of first-degree friends</li> <li>- Density</li> <li>- 2-Betweenness</li> </ul>	<ul style="list-style-type: none"> <li>- Ego network size is positively correlated to video popularity</li> <li>- Ego network density and betweenness are negatively correlated to video popularity</li> <li>- Viewership of the last two days positively influences video popularity</li> <li>- Number of users who “favored” the video also positively correlated</li> </ul>

Author/s (Year) [Journal]	Research Focus	Theoretical Background	Outcome Analyzed	Sample	Method/ Analysis	Independent Variables	Main Findings
Gonzalez, Claro and Palmatier (2014) [Journal of Marketing]	Effect of brokerage and density in informal and formal firm networks on a relationship manager's performance	Structural holes theory (Burt 1992) Social capital theory (Coleman 1988)	Relationship managers' performance measured as their sales growth	n = 101 relationship managers Data on the informal and formal ego networks obtained from organizational charts of a b2b firm and interviews with 472 employees on the informal network	Moderated regression/ ordinary least squares approach	<p><i>Main variables:</i> Brokerage and density in formal and informal networks</p> <p><i>Moderating variables:</i> Cross-network synergy (brokerage measure in one times density in other network) and overlap-network synergy (brokerage or density times average multiplexity)</p>	<p>- Both brokerage and density in formal networks positively influence performance</p> <p>- Brokerage in informal networks and density in formal networks (cross-network synergy) improves performance</p> <p>- Results increase significantly if there is a high network overlap (multiplexity)</p>

Author/s (Year) [Journal]	Research Focus	Theoretical Background	Outcome Analyzed	Sample	Method/ Analysis	Independent Variables	Main Findings
Rodan (2010) [Social Networks]	Tests what mechanism mediates the relationship between structural holes and managerial performance	Structural holes theory (Burt 1992)	Managerial performance assessed by senior management	n = 106 managers at a Scandinavian telecom-munications service provider  Data was obtained through classical ego network surveys	Linear regressions	<ul style="list-style-type: none"> <li>- Ego-network density</li> <li>- Alter-knowledge heterogeneity</li> <li>- Innovativeness</li> </ul>	<ul style="list-style-type: none"> <li>- Innovativeness mediates the relationship between knowledge heterogeneity, network structure and performance</li> <li>- Other mechanisms (e.g. information arbitrage, autonomy) are only significant when innovativeness is not included in the model</li> </ul>

Author/s (Year) [Journal]	Research Focus	Theoretical Background	Outcome Analyzed	Sample	Method/ Analysis	Independent Variables	Main Findings
Aral and Van Alstyne (2011) [American Journal of Sociology]	Effect of frequency of interaction (bandwidth) and structural holes (network diversity) in a network on diversity of information, total non-redundant information and performance	Structural holes theory (Burt 1992) Strength of weak ties theory (Granovetter 1973)	- Diversity of information (ID) - Total non-redundant information (NRI) - Employee performance	n = 73 recruiters Recruiters ego networks constructed out of e-mail messages exchanged by 87% of the employees of an executive recruiting firm in the US from Oct 1 <sup>st</sup> 2002 to March 1 <sup>st</sup> 2003 and Oct 1 <sup>st</sup> 2003 to March 1 <sup>st</sup> 2004	Several linear regressions DV: (1) Bandwidth (B) (2) Network Diversity (ND) (3) ID (4) NRI (5) Performance	(1) ND, structural equivalence (2) Structural equivalence, B (3) ND, structural equivalence, B, refresh rate x B, topic space x B, information overlap x ND (4) same as (3) but difference in control variables (5) ND, B, NRI  + several control variables in each model such as human capital or total number of incoming e-mails	- Strong negative relationship between ND and B and a strong positive relationship between structural equivalence and B - Both ND and B affect ID and NRI but ND has a greater effect on ID and B a greater effect on NRI - NRI is positively related to performance - ND is significantly correlated to performance even when NRI is taken into account



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