**LOOKING ACROSS BORDERS: HOW COGNITIVE ABILITIES AFFECT ADVICE SEEKING NETWORKS**

**Abstract**

We study how cognitive abilities and complementarity in competence contribute to advice network dynamics in an MBA cohort (N=110). Building on social exchange theory and insights from the cognitive abilities literature, we explore how verbal and quantitative abilities on advice seeker and advisors sides add to formation of advice relationships. Stochastic actor based modeling of social network dynamics (RSiena) reveals verbal & quantitative abilities and complimentary specialization contribute to advice seeking dynamics. The insights of this study contribute to our understanding of how diversity in terms of different specializations and cognitive abilities contributes to the knowledge sourcing behaviors within organizations.

***Keywords:*** social networks, advice, longitudinal, stochastic actor-based modeling of social network dynamics, cognitive abilities

**INTRODUCTION**

Information seeking and sharing is essential in any organization to resolve problems and address opportunities that require coordinated effort or integration of disparate expertise (Borgatti & Cross, 2003). Advice networks are relationships that transmit resources and facilitate information and knowledge exchange by providing guidance, assistance and insights on how work is best done within the organizations, which enhances individuals’ and groups’ performance (Sparrowe et al., 2001). Advice networks carry a range of valuable outcomes for individuals, groups and organizations: they contribute to individual performance (Sparrowe et al., 2001) and career success (Fang et al., 2015), emergence of employment preferences (Snijders, Lomi & Torlo, 2013), turnover intentions (Vardaman et al., 2015), creativity (Li et al., in press), gender biases (Brands et al., 2015) and the sense of psychological safety within team (Schulte, Cohen & Klein, 2012). Appreciation of the outcomes of the social network structure also raises the question on how advice networks come into being, which calls for investigation of antecedents of network structure emergence (cit Kilduff). Recent research identified a range of individual, social and contextual factors and processes that shape the dynamics of advice networks. Evidence points that individuals’ characteristics such as personality (Fang et al., 2015) and values (Klein et al., 2004) contribute to the advice network emergence. However, until know we know little on how the diversity of cognitive abilities – “the repertoire of intellectual (or cognitive) skills available to the person at a particular point in time” (Humphreys, 1989: 194) - contributes to advice seeking as a knowledge sourcing behavior.

Cognitive ability measures are known to predict performance in work and educational settings, and knowledge acquisition and processing behaviors contribute to our understanding of processes that explain how cognitive abilities impact performance. “The need to acquire knowledge and skill both formally and informally in work and educational setting as well as apply previously acquired knowledge and skill to perform tasks provides one major explanation for why cognitive ability measures predict performance in both educational and work settings.” (Kuncel, Crede & Thomas, 2007: 54). In this process the cognitive abilities of the advice seeker and the advisor play a key role.

The literature also indicates that advice seeking is a double-edge sword. While informal relationships reduce the cost of information acquisition within the organizations (Lazega, Mournier, Snijders, & Tubaro, 2012) and provide a range of valuable insights on potential problem solutions, the social exchange theory (Blau 1955, 1964) suggests that advice provision occurs at a social cost. In particular, Blau (1955, 1964) suggests that advice seekers choose advisor based on his or her status, and thus trade status recognition for advice. This status recognition provides an incentive for advice givers to share their knowledge and insights. Thus, advice seeking reinforces informal status hierarchies within the organization and might come at a cost to both the advice seeker and advisor, who trade knowledge for status.

A range of potential factors has been suggested to lower this ‘exchange rate’ between advice and status. Lazega et al. (2012) suggest that similarity on individual characteristics – homophily - in terms of demographic or value similarity calls for solidarity between the advisors and advice seekers and leads to a situation where advisors and advisees are more likely to be similar.

In this article we focus on the role of diversity of cognitive abilities in shaping of the advice seeking dynamics. To better pinpoint the role of the individuals’ cognitive abilities, we separate the impact of individuals’ characteristics from social processes that might impact advice seeking. We also account for the available knowledge base and control for previous specialization. We explore these processes in the highly diverse setting – an MBA program – where knowledge acquisition is of crucial importance. In particular, we posit that advice seekers quantitative abilities positively affect advice seeking. Moreover, we suggest that there is a negative curvilinear relationship between the verbal abilities of the advice seeker and the formation of the advice seeking relationship. Finally, we suggest that people would prefer to seek advice from others with complementary expertise as measured by the professional background.

Our investigation yields a range of important contributions. First, our investigation adds to the literature on microfoundations of organizational networks (Tasselli, Kilduff & Menges, 2015) by specifying the role of intelligence in social network dynamics. Second, we answer calls to assess how specific cognitive abilities contribute to particular workplace that affect performance in the workplace (Schneider & Newman, 2015) by zooming on the role of cognitive abilities in information sourcing behavior.

**METHODS**

**Participants and setting**

***Setting*.** We studied advice dynamics in cohort of 110 MBA students program in one of the top ten European universities. The program lasts for one year, and participants are randomly assigned into diverse teams to work together on the projects during all courses in the first semester. The setting provides a welcome opportunity to test the effects of cognitive abilities on advice seeking as a knowledge sourcing behavior. To prepare students for the complex and ill-defined problems encountered in the business world, business schools often try to simulate such settings and engage participants in a range of experiences that foster and develop information gathering, coordination and problem-solving skills (Kuncel, Crede & Thomas, 2007), as well as a range of interpersonal behaviors aimed at collecting, organizing and processing such information. Business schools directly (through assignments and exercises) and indirectly (through context and application of assignments in work context) foster knowledge acquisition and processing skills. Thus, advice seeking plays an essential role in this context.

***Participants***. 109 students filled in the questionnaires containing social network data (1 participant dropped out of the program). Sample (23% female) was highly diverse in terms of nationality (33 nationalities; 30% of participants came from Europe, 41% from Asia, 23% from North America; 5% from South America; 2% from other places) and previous specialization. Two students were from the country where the MBA took place. Students had a background in accounting (4,5%), business administration (18.2%), economics (15,5%), engineering (29.1%), IT (5.5), science (8.2%), law (3.6%), marketing (6.4%), social sciences (9.1%). The mean age of the participants was 30.82 (*SD* = 3.12, range 25-38 years).

***Procedure****.* As a part of the personal development project, participants filled in an online social network survey at the start of the year after the introduction period and at the end of the semester before the participants changed groups. Participants were assured that their data would be handled confidentially and would be anonymized after the data matching procedure. The data has been communicated back to the participants after the second data collection point in the aggregated, anonymized form.

**Measures**

***Advice seeking****.* Study participants received an online questionnaire with a list of all participants and were requested to indicate “To whom do you go to when you need expert advice on how to solve a problem in your school work?” Respondents could nominate as many people as they wish. The questionnaire has been administered twice: after the introduction period at the start of the year and at the end of the semester. At each measurement point, we compiled a binary matrix of directed advice seeking ties (advice seeking was coded as 1). Responses were obtained from everyone (t1: 110, t2: 109 individuals), apart from one participant who dropped out of the program.

***Verbal ability.*** We included the score for the verbal ability from GMAT test, obtained from official university records. The test has been completed prior to the start of the MBA program. Scores ranged from 16 to 46, with a mean score of 32.16 (SD 6.86).

***Quantitative reasoning*.** We used quantitative part of GMAT scores to proxy participants’ ability to solve quantitative problems and analyze information. Grades ranged from 26 to 51, with a mean grade of 43.81 (SD 6.04).

***Analytical skills***were captured with help of the Analytical Writing Assessment (AWA) that is the part of GMAT. AWA assesses the ability to analyze and critique the reasoning behind an argument. The average AWA scores were 4.68 (SD 0.74, range 3.00 – 6.00).

***Controls****.* Consistent with previous research (e.g. Brass 1985, Ibarra 1992, Selfhout et al. 2010), we controlled for demographics - gender (female = 1), age, nationality, and language. To proxy the competence of participants, we controlled for the level of their previous degree (Diploma, Bachelor, Master, PhD or other) and the previous degree specialization (accounting, business administration, economics, engineering, IT, science, law, marketing, social sciences). Because participants had a higher chance to interact within their teams, in the analysis of complete advice networks we controlled for whether participants belonged to the same team.

**Analysis**

***R-based Simulation Investigation of Empirical Network Analysis (RSiena)*.** We applied R-based Simulation Investigation for Empirical Network Analysis (RSIENA), version 1.2.4 to understand how actors’ characteristics affect network formation processes. This method (Snijders, van de Bunt and Steglich 2010) allows to separate the impact of individual factors from social influences. We focus on verbal, analytical and quantitative abilities that contribute to formation of boundary-spanning advice seeking, and distinguish these effects from relational mechanisms (e.g. Matthew effect – popular people are getting even more popular) that also influence network formation.

RSiena assumes that networks continuously evolve between two measurement points, which adds to the realism of the model (Snijders et al., 2010). To specify, networks’ change follows a Markov process: the previous state of the network influences the current one. The change is modeled step by step: at each step, an actor (in this case research participant) chooses whether to keep or change his or her relationships, one at a time. The direction of relationships is also taken into account; RSiena allows to distinguish between advice seeker (ego parameter) and the advisor (alter parameter). In RSiena modeling, actors need to be aware of each others’ existence, which is consistent with the MBA setting.

We chose RSiena to test the suggested effects for three main reasons. First, it allows us to represent continuous development of boundary-spanning advice seeking relationships among MBA participants. Second, RSiena helps us to define processes of advice seeking by assuming that actors are in charge of whom they approach. Finally, the model allows us to separate individual cognitive factors from the influence of social processes.

**Model specification**

We model the influence of verbal ability, quantitative reasoning and analytical skills on creation and maintenance of advice seeking ties. Therefore, we incorporate individual (actor covariate) effects and network structural effects into the model.

***Actor covariate effects:*** As we are primarily interested in effects of verbal, analytical and quantitative abilities on formation of advice seeking ties, we specify individual covariates for each of the abilities as: (1) *ego effect* models the tendency to seek advice; we label positive effect as *activity*,and negative effect as *withdrawal*; (2) *alter effect* stands for propensity to seek advice from others with a particular ability; we label positive effect *aspiration* and negative one *rejection*.

In other words, a significant ego parameter on analytical ability would mean that participants who score higher on analytical ability would demonstrate activity more, and seek others for advice more over the course of the study. A negative ego parameter would mean that the participant would tend to avoid advice seeking over the course of the study or dissolve advice seeking ties. A positive alter parameter on analytical ability would mean that MBA students would aspire to seek advice from people high on analytical ability, and a negative alter parameter would mean that people would avoid (reject) seeking advice from verbally adept people.

In line with previous recommendations for continuous variables (Snijders & Lomi, 2018) we also add curvilinear effects into the model specification and an interaction term between ego and alter effects.

We also incorporate curvilinear preferences in sending out ties by adding an *ego squared* parameter, and curvilinear preference to choose advisers who fall into the range of particular characteristics as *alter squared effect*. To check whether participants choose advisers similar to themselves, we add an *ego\*alter* parameter. A positive parameter stands for homophily (similarities attract), a negative one - for heterophily (people choose advisors with complementary skills).

***Structural effects*.** Additionally, we add the following effects to capture social influences on advice seeking dynamics (Ripley et al., 2018):

*1) Out-degree effect.* Density in networks imposes constrains on the opportunity to connect to others. To account for this, we add an out-degree effect. This default effect stands for the intercept in the model specification.

*2) Reciprocity.* People tend to reciprocate relationships, and reciprocity parameter measures that (Skvoretz & Agneessens, 2006).

*3) Effects assessing transitivity* measure whether indirect ties improve the odds of relationship formation. *Transitive reciprocated triplets* measure the tendencies for triadic closure; we include the effect to account for the fact that relationships within transitive groups are usually less frequently reciprocated than relationships not embedded into groups (Block, 2015). We also add GWESP forward-forward (*GWESP FF*) effect to assess transitive closure; we prefer GWESP FF over the transitive triplets effect as it takes into account the number of available intermediaries.

*4) Degree-related effects*. Reputation effects could be driving advice tie formation in the sample. *Indegree-popularity effect* allows us to proxy that: overtime participants with a lot of incoming ties would be accumulating even more ties. This effect has been labeled Matthew effect – rich are getting richer (Merton, 1968). With help of this effect we model whether the popular advisors would accumulate advisees at higher rate than the rest.

*Outdegree activity* indicates whether people who seek advice would continue to seek more advice (expansiveness bias, Feld & Carter 2002).

*Rate parameters:* RSiena automatically adds a network *rate* parameter into all RSiena estimations. The rate parameter assesses the frequency with which actors alter their relationships.

**RESULTS**

**Descriptive statistics for individual variables**

Table 1 describes key variables in our sample. Apart from quantitative skills (skewness -1.12) variables are approximately normally distributed (skewness ±1). Verbal abilities decrease with age (Pearson's *r* = -.32, *p* < 0.01), and are correlated with analytical skills (Pearson's *r* = .51, *p* < 0.01).

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Insert Table 1 around here

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**Descriptive statistics for network change**

110 participants reported 857 unilateral advice ties at time point 1, and 973 advice ties at time point 2. One participant dropped out of the program. The average degree and density increased over time. The Jaccard index (0.22 for advice seeking) indicates that participants change advisers a lot in between measurement points. The stability within networks is low but sufficient (Ripley et al., 2017).

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**Results of RSiena analysis**

***Main effects****.* We explored how verbal, quantitative and analytical abilities affect formation and maintenance of advice seeking relationships, controlling for the social influence processes. Results in Table 3 indicate that people who score high on verbal abilities turn to others for advice less (*verbal ego* parameter: advice seeking est.=-0.0087, *p*<0.05). The squared ego parameter for verbal abilities (advice seeking est.=0.0011, *p*<0.01) indicates normative activity: ego effect is more pronounced at the extreme ends of the scale (people in the middle range of verbal skills seek advice somewhat less). There is also heterophily (complementarity) in verbal abilities (advice seeking est.=-0.0011, *p*<0.05): people who lack verbal skills seek advice from those who display high verbal abilities. We also observe that individuals in the mid-range of quantitative skills engage less in advice seeking than those who score at the both ends of the quantitative scale (*squared ego*: advice seeking est.=0.0012, *p*<0.05).

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Insert Table 3 around here

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***Structural parameters****.* Advice relationships in our sample tended to be reciprocated (reciprocity, advice seeking est.=1.3309, *p* < 0.001). We also considered few processes of triadic closure (“advisers of my advisers are my advisers”) to check whether the presence of indirect advising relationships improves odds of seeking advice. The positive geometrically weighted edgewise shared partners parameter (GWESP FB: advice seeking est.=0.72, *p*<0.05) indicates that participants were more likely to seek advice from someone whom they share a common advisor with. The negative *transitive reciprocated triplets parameter* (advice seeking est.=-0.1619, *p* < 0.05) indicates that ties within transitive groups are less likely to be reciprocated than the relationships not embedded into groups (Block, 2015).

We find evidence for closure (*balance* effect, advice seeking est.=0.0652, *p* < 0.01), controlling for the opportunities available for participants to reach out. The positive estimate for the *number of actors at distance 2* (advice seeking est.=0.0351, *p*<0.1) is a reverse indicator of network closure. In combination with the balance effect, this parameter reveals that while MBA participants would be more likely to seek advice from others if they already established a relationship to a common adviser, they still had sufficient opportunities to get advice elsewhere. Surprisingly, we find evidence for the reversed Matthew effect (negative *indegree popularity* effect: advice seeking est.=-0.04, *p*<0.01). In other words, people seek less advice over time from popular advisors. Our results indicate that people who seek a lot of advice would continue to do so (o*utdegree activity* effect:advice seeking est.=0.07, *p*<0.001; boundary spanning est.=0.0835, *p*<0.001). *Truncated outdegree* (advice seeking est.=-2.26, *p*<0.001) allows to balance for isolates (people without any ties) in the estimation.

***Controls.*** We find no evidence that gender plays a role in advice seeking in this sample (gender ego est.=0.01, *ns*; gender alter est.=0.08, *ns*; gender homophily est.=0.11, *ns*). While older group members sought advice more (*age ego* effect:est.=0.02, *p*<0.01), participants were less likely to seek advice from older group members (*age alter* effect:est.=-0.03, *p*<0.05;). Same nationality, language, level of the degree did not affect advice seeking. Participants were more likely to seek advice from others who had a different professional background than them (*same previous degree specialization* effect:est.=-0.1208, *p*<0.1).

**DISCUSSION**

Answering calls to further explore the evolution of the advice relationships (Tröster, Parker, van Knippenberg & Sahlmüller, 2018), we found that individuals’ verbal and quantitative abilities affect the patterns of advice seeking. High scores on verbal ability in our model are related to lower odds advice seeking. Team members exhibit normative preference for advisors’ verbal abilities and prefer to seek for advice from others who score in the mid-range of verbal abilities. Individuals who score high on quantitative scale are more likely to seek advice.

Additionally, we shed light on the social processes that contribute to dynamics of advice seeking networks. We found that social processes guide knowledge seeking behavior of individuals: the presence of joint advisors enables the emergence of new advice seeking ties. We were surprised to find that popular advisors decreased in their popularity over time, while active advice seekers continued to seek a lot of advice. Our participants sought advice from others who had a different specialization from themselves, suggesting complementarity in knowledge exchange.

Our study contributes to organizational social network theory (Borgatti & Foster, 2003; Borgatti & Halgin, 2011; Borgatti, Mehra, Brass & Labianca, 2009; Brass, Galaskiewicz, Greve & Tsai, 2004; Kilduff & Tsai, 2003; Tasselli, Kilduff, Menges, 2015) in two key ways. In particular, we add to research on micro-foundations of organizational social network dynamics (Tasselli, Kilduff, Menges, 2015) by spelling out how individual differences contribute to emergence of networks (Burt, Kilduff & Tasselli, 2013), and how resulting organizational networks in turn enable and constrain individuals’ behavior.

***Strengths and limitations***

This paper covers new territory by introducing cognitive abilities as an antecedent of advice seeking networks and thus sheds light on the origins of knowledge seeking behavior within organizations. We also identify longitudinal design, analytical approach and high response rate as papers’ strengths. However, we refrain from generalizing to other contexts, as participants’ GMAT scores contributed to selection into the MBA program (the theoretical range for GMAT is considerably larger, and participants with higher scores were more likely to get an offer).

Further research could further differentiate how the quality of the advice provided affects the subsequent advice seeking and explore whether the participants rewire their advice relationships in order to seek advice from people who tend to provide a better-quality advice (Tröster, Parker, van Knippenberg & Sahlmüller, 2018).

***Limitations***

Our study has been conducted in a cosmopolitan setting in the Netherlands where people from multiple cultures collaborate together and where locals were in a minority. While this allows to test the generalizability of current theories in new settings, the cosmopolitan nature of the setting might have contributed to the fact that nationality did not play a role in advice seeking. Further research might want to unravel the role of social identity in emergence of social networks. On the other hand, Dutch cultural norms of involving everyone into decision making and consensus seeking (‘poldermodel’) might have affected the density of the advice seeking networks. So future research might address the role of cultural norms in advice seeking dynamics.

As all network researchers, we faced a trade-off between the obtaining a high response rate necessary for the dynamic analysis of networks and including the broad range of known predictors. Due to the constrains of the setting we had to omit other variables known to impact the social network dynamics, such as personality and values (Klein et al., 2004, Schulte et al., 2012), turnover intentions (Tröster et al., 2018) or friendship (Tröster et al., 2018; Lomi, Snijders & Torlo, 2012).

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*Table 1. Descriptive statistics for individual variables*

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Mean | | SD | | 1 | | 2 | | 3 | | 4 | | | 5 | |
| 1. Gender | 0.23 | | 0.42 | | -- | |  | |  | |  | | |  | |
| 2. Age | 30.82 | | 3.13 | | -0.13 | | -- | |  | |  | | |  | |
| 3. Analytical skills | 4.68 | | 0.74 | | -0.13 | | -.32\*\* | | -- | |  | | |  | |
| 4. Quantitative skills | 43.81 | | 6.04 | | -0.04 | | 0.09 | | -0.03 | | -- | | |  | |
| 5. Verbal skills | 32.16 | | 6.86 | | -0.11 | | -0.15 | | .51\*\* | | -0.12 | | | -- | |
| *\*\*. Correlation is significant at the 0.01 level (2-tailed).* | | | | | | | | | | | | |

*Table 2. Descriptive statistics for network change*

|  |  |  |
| --- | --- | --- |
|  | Time 1 | Time 2 |
| Boundary-spanning advice seeking |  |  |
| Density | 0.071 | 0.083 |
| Average degree | 7.79 | 9.00 |
| Number of ties | 857 | 973 |
| Jaccard index | 0.22 |  |

*Table 3. Results of the RSiena analysis*

|  |  |  |  |
| --- | --- | --- | --- |
|  | Advice seeking | | |
| Parameter | Est. | SE |  |
| **DV: Friendship** |  |  |  |
| *Rate parameters* |  |  |  |
| Basic parameter rate | 41.8205 | 3.8141 | \*\*\* |
| *Structural parameters* |  |  |  |
| Outdegree (density) | -2.8698 | 0.2910 | \*\*\* |
| Reciprocity | 1.3309 | 0.1414 | \*\*\* |
| Transitive recipr. triplets | -0.1619 | 0.0756 | \* |
| Balance | 0.0652 | 0.0186 | \*\*\* |
| Number of actors at distance 2 | 0.0351 | 0.0197 | † |
| GWESP I -> K -> J (69) | 0.3116 | 0.2380 |  |
| GWESP I <- K <- J | -0.1018 | 0.1824 |  |
| GWESP I -> K <- J | 0.7196 | 0.3598 | \* |
| Indegree - popularity | -0.0390 | 0.0133 | \*\* |
| Outdegree - activity | 0.0725 | 0.0183 | \*\*\* |
| Outdegree - trunc (isolates) | -2.2550 | 0.4066 | \*\*\* |
| *Controls* |  |  |  |
| Gender alter | 0.0808 | 0.0806 |  |
| Gender ego | 0.0103 | 0.0702 |  |
| Same gender | 0.1129 | 0.0701 |  |
| Age alter | -00273 | 0.0124 | \* |
| Age squared alter | 0.0017 | 0.0028 |  |
| Age ego | 0.0216 | 0.0080 | \*\* |
| Age squared ego | 0.0011 | 0.0022 |  |
| Age ego \* alter | 0.0034 | 0.0024 |  |
| Same nationality | 0.0932 | 0.1161 |  |
| Same language | 0.0369 | 0.0828 |  |
| Same group | -0.1489 | 0.1339 |  |
| Degree level alter | 0.0279 | 0.0219 |  |
| Degree level ego | -0.0190 | 0.0176 |  |
| Same previous degree specialization | -0.1208 | 0.0722 | † |
| *Abilities* |  |  |  |
| Verbal alter | 0.0060 | 0.0060 |  |
| Verbal squared alter | -0.0012 | 0.0006 | \* |
| Verbal ego | -0.0087 | 0.0039 | \* |
| Verbal squared ego | 0.0011 | 0.0004 | \*\* |
| Verbal ego \* alter | -0.0011 | 0.0005 | \* |
| Analytical skills alter | -0.0635 | 0.0546 |  |
| Analytical skills squared alter | 0.0588 | 0.0520 |  |
| Analytical skills ego | -0.0552 | 0.0391 |  |
| Analytical skills squared ego | 0.0270 | 0.0419 |  |
| Analytical skills ego \* alter | 0.0026 | 0.0481 |  |
| Quantitative skills alter | 0.0053 | 0.0067 |  |
| Quantitative skills squared alter | -0.0004 | 0.0007 |  |
| Quantitative skills ego | -0.0037 | 0.0055 |  |
| Quantitative skills squared ego | 0.0012 | 0.0006 | \* |
| Quantitative skills ego \* alter | 0.0002 | 0.0006 |  |

*Significance levels: † p<0.1, \* p<0.05, \*\* p<0.01, \*\*\* p<0.001.*

*The estimation converged well: t-ratios for convergence are all below 0.1 and the overall maximum convergence ratio is 0.19.*