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Expertise and specialization in organizations: a social network analysis

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ABSTRACT

Organizations rely on their employees' expertise (i.e. very high domain-specific competence relative to peers) and specialization (i.e. moderate to high competence in tasks for which no direct peers are responsible) to foster innovation and knowledge-sharing processes. While previous research demonstrated the pivotal role of experts and specialists, there remains scant knowledge on their skill profiles and embeddedness in organizational networks. Employing social network analysis ($N = 344$), we explore the relationships between the reception of advice requests – quantified by in-degree centralities – and self-assessed skills, expertise, and specialization. The results suggest a halo effect, as proficiency in one skill bundle is related to advice requests in other skill bundles. Furthermore, we use an exponential random graph model (ERGM) to provide evidence of similarities in skills, tenure, and leadership responsibility between advice-giver and advice-seeker. Finally, we use optimal matching analyses to compare skill profiles of individuals in our sample with theoretically derived ideal types of skill profiles for experts and specialists. The study underscores the need to further investigate expertise and specialization, emphasizing the importance of distinguishing between diverse knowledge carriers and skill profiles within career development, talent management, and knowledge management.

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1. Introduction

Organizations' success relies on employees with the right skills to deliver superior goods and services (Becker & Murphy, 1992; Salas & Rosen, 2010). However, the breadth and depth of skill sets differ among employees. Thus, organizations utilize skill models or competence models to define and keep track of each employee's skill set or skill profile (Chouhan & Srivastava, 2014; Dalton, 1997; Kansal et al., 2012; see also Köhler & Rausch, 2022; Sternberg, 2005). In doing so, organizations often distinguish between experts and non-experts (Gruber & Harteis, 2018; Salas & Rosen, 2010) or between specialists and generalists (Fahrenkopf et al., 2020; Teodoridis et al., 2019). Expertise refers to very high domain-specific competence relative to peers with the same tasks, as manifested by "continuous outstanding performance" across tasks in a specific domain (Gruber, 1991, p. 23; see also Chi, 2006). In contrast, specialization primarily refers to medium to high competence in tasks for which one is solely responsible (Köhler & Rausch, 2022).

Individuals' expertise and specialization partly determine whether peers approach them for advice; thus, expertise and specialization are important resources for work-related learning (Becker & Murphy, 1992; de Toni & Nonino, 2010; Köhler & Rausch, 2022; Lave & Wenger, 1991; Palonen & Hakkarainen, 2014; Salas & Rosen, 2010; Tynjälä, 2013). We conceptualize individuals' advice-seeking as a social network in an organization. Social networks permeate formal work units and departments (Kijkuit & van den Ende, 2010; Lamertz, 2006; Palonen & Hakkarainen, 2014) and serve as important resources for enhancing performance (Calciolari et al., 2017; Lamertz, 2006), facilitating learning (Noe et al., 2014; Tynjälä, 2013), offering support for difficult tasks (Calciolari et al., 2017; Greer et al., 1998), and fostering training transfer (Richter & Kauffeld, 2020). Although expertise and specialization are of interest in various scientific domains, such as expertise research and individual-/team-focused organizational learning research, research offering explicit conceptualizations of expertise and specialization – and integrating these concepts into the literature on social networks in organizations – is lacking in work and organizational psychology. This conceptualization and clarification of both constructs is relevant in the study of employees' skill retention, skill development, and training needs and offers avenues for a better understanding of advice seeking and advice giving in organizations. Specifically, we highlight three research gaps that we aim to fill with our study. First, previous research identified the roles of social status (Agneessens & Wittek, 2012; Lazega et al., 2012) and differences or similarities in skill sets (DiVincenzo & Mascia, 2017; Lőrincz et al., 2020) in advice seeking within social networks. However, it remains underexplored whether employees receive requests only for tasks related to their high-level skills or whether requests spill over to other skills. In social network analysis (SNA), this connectedness of advice seeking across skill domains is measured through in-degree centrality (Knoke & Yang, 2020). Thus, in our first research question (RQ1), we are interested in how an individual's in-degree centrality regarding a given skill bundle relates to the self-assessed skills in this skill bundle and to the in-degree centrality of other skill bundles. Second, while several factors (e.g., tenure and age) are known to influence the likelihood of being approached by peers for advice requests

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(Nebus, 2006; Ridgeway, 2001), to the best of our knowledge no previous work has employed the distinct roles of expertise and specialization to understand the emergence of advice-seeking networks. Hence, our second research question (RQ2) addresses how social processes and individual characteristics are related to patterns of ties in advice-seeking networks. Answers to both RQ1 and RQ2 can help organizations to understand advice-seeking behaviour and guide employees' advice seeking. Third, while experts and specialists can be differentiated based on their social-network position (de Toni & Nonino, 2010), it remains unclear whether employees' actual skill profiles match the hypothesized skill profiles of experts and specialists. Consequently, our study compares theoretically derived ideal types of skill profiles for experts and specialists with their occurrences in an advice-seeking network. Thus, with our third research question (RQ3), we explore whether an employee's skill profile is a useful criterion, in addition to network position, for identifying experts and specialists. Thereby, we follow Salas and Rosen's (2010, p. 123) call to develop "methods for identifying experts" while additionally identifying their counterparts, specialists, in organizations.

We address these research questions through a quantitative study combining data from a questionnaire with items for 29 skills divided into three skill bundles, information from the participating organization's database, and ego network data that we collected from employees in the participating organization. We use the ego network data to infer the complete network in the organization (Smith, 2012, 2015). We analyse these data using methods from SNA and sequence analysis. Based on SNA, we compute the employees' in-degree centralities for skill bundles. In addition, we employ an exponential random graph model (ERGM) to investigate which variables and similarities among peers result in being asked for advice. Lastly, we adapt an approach from sequence analysis to compute the distances between actual employees' skill profiles and theoretically derived ideal skill profiles of experts and specialists (Studer & Ritschard, 2014).

2. Domains, expertise, specialization, and social networks in organizations

2.1. Expertise and specialization in organizations

Expertise refers to very high domain-specific competence relative to peers with the same tasks, as manifested by "continuous outstanding performance" across tasks in a specific domain (Gruber, 1991, p. 23; see also Chi, 2006; Ericsson, 2018b, 2018b; Jacobs & Washington, 2003; Jacobs & Park, 2009; Sternberg, 2005). Employees typically develop expertise through active engagement in a domain (e.g., sales) over a long period of time (Billett et al., 2018; Ericsson, 2018b, 2018b; Gruber, 1999). In contrast, specialization primarily refers to medium to high competence in a domain or subdomain for which one is solely responsible. This responsibility may be defined in an organizational chart or may be an agreed-upon division of labour among peers (Becker & Murphy, 1992; Jacobs & Park, 2009; Jacobs & Washington, 2003; Köhler & Rausch, 2022; Mieg, 2001; Taylor, 1911; Wong, 2008).

While extensive specialization might increase productivity (Becker & Murphy, 1992) and learning within teams (Bresman & Zellmer-Bruhn, 2013), it must be weighed against the risk of employees and their knowledge leaving an organization or extensive retraining when the current job becomes obsolete (Dolot, 2018; Lyons et al., 2015; Wajcman, 2017; see also Nonaka & Konno, 1998). Hence, within an organization, employees may have different levels of specialization. First, a "lone fighter" specialist can be an employee who is solely responsible for a single domain or subdomain, such as a lawyer in an organization or a single controller in sales (Rausch et al., 2015, p. 452; see also Mieg, 2001). Second, specialization can also arise from a division of labour among peers within a shared domain or subdomain that may not be evident from an organizational chart (e.g., sole responsibility for tasks related to customer complaints in the subdomain of business-to-business sales). Thus, while the development of expertise requires sustained active engagement (Ericsson, 2008, 2018b; Gruber, 1999), specialization can be the result of an ad-hoc division of labour. In practice, such specialists might be perceived and labelled as experts by their peers (Köhler & Rausch, 2022; Mieg, 2001). However, a specialist's set of tasks is usually perceived as *different* by colleagues in his or her work environment. Furthermore, in practice, it is common to develop a mixture of expertise and specialization for certain tasks within a subdomain (Ackerman, 2011; see also Becker & Murphy, 1992). Hence, the concepts of expertise and specialization are difficult to distinguish in practice.

2.2. Expertise and specialization in the context of domains

Expertise and specialization are defined in the context of domains. Domains evolve around an organization's "constitutive problems", which can never be exhaustively solved; examples include the "elimination of disease" in medicine, the end of "ignorance" in teaching, or total customer satisfaction and the creation of revenues in sales (Bereiter & Scardamalia, 1993, p. 97; see also Köhler & Rausch, 2022). Domains are further defined by knowledge and tools which are subject to change and development (Ackerman, 2011; Alexander, 1992; Bereiter & Scardamalia, 1993; Köhler & Rausch, 2022; Maggioni & Alexander, 2011). Such knowledge and tools are necessary for individuals to participate in solving the constitutive problem and its related task bundles (Ackerman, 2011; Alexander, 1992; Bereiter & Scardamalia, 1993; Maggioni & Alexander, 2011; see also Hambrick, 1981; Shavelson, 2009; Taylor, 1911). Furthermore, domains can be divided into subdomains, such as business-to-business and business-to-customer sales. Hence, a subdomain comprises a narrower task bundle and corresponding skills. However, the term *domain* is predominately used in the expertise literature, whereas the term *functional area* is predominantly used in practice and in the organizational learning literature. Functional areas include, among others, production, marketing, human resources, and sales (Hambrick, 1981). While domains and subdomains are defined rather narrowly, the term *functional area* seems to be defined more broadly and is more organization-specific. However, from both perspectives, sales contains the subdomains or areas of sales control, business-to-business sales, and business-to-customer sales, which all involve different degrees of overlapping knowledge and tools. Hence, domains and functional areas are, to a large extent, synonymous, but they are used to varying degrees in different fields. For the purposes of the present study, we use the terms *domain* and *subdomain*.

2.3. Identifying experts and non-experts in expertise research

Regarding individual performance in domains and subdomains, experts and non-experts (e.g., novices and intermediates) are investigated in expertise research (Dreyfus & Dreyfus, 1986). Often, non-experts and experts are compared to find differences between the groups (Dreyfus & Dreyfus, 1986; Gruber, 1991; Gruber & Harteis, 2018). Furthermore, every employee within the same domain (e.g., controlling) who is not an expert is considered a non-expert, and such employees might eventually become experts over time or stay non-experts (Billett et al., 2018; Dreyfus & Dreyfus, 1986; Gruber, 1999). The goal of this stream of literature within expertise research is to establish a course of action for non-experts to advance towards becoming experts, to identify hindering and supporting factors, and to observe the course of maintenance of expertise over time (Dreyfus & Dreyfus, 1986; Gruber & Harteis, 2018; see also Salas & Rosen, 2010).

2.4. Identifying specialists and generalists in organizational learning

Organizational learning focuses on individual-, team-, or organizational-level learning (Huber, 1991), where learning at each of these three levels is connected to the learning at the other levels (Huber, 1991; Tanyaovalaksna & Li, 2013). Within the individual- and team-focused organizational learning research, there is also an ongoing discussion on differentiating specialists and generalists in terms of the division of labour (Anderson, 2012; Fahrenkopf et al., 2020; Golembiewski, 1965; Ivanova et al., 2019; Postrel, 2002; Teodoridis et al., 2019; Wang & Murnighan, 2013; see also Lansbury, 1976). The common thread in discussions of specialists is high competence in a small task bundle, a single subdomain, or a narrow domain (Anderson, 2012; Fahrenkopf et al., 2020; Ivanova et al., 2019; Postrel, 2002; Ryan, 1963, as cited in Golembiewski, 1965, p. 135; Teodoridis et al., 2019; Wang & Murnighan, 2013). Regarding generalists, the common thread is medium competence in several related or unrelated domains or subdomains (Anderson, 2012; Fahrenkopf et al., 2020; Ivanova et al., 2019; Postrel, 200; Ryan, 1963 as cited in Golembiewski, 1965, p. 135; Teodoridis et al., 2019; Wang & Murnighan, 2013). The goal of differentiating specialists and generalists is to increase productivity and to allocate personnel more efficiently.

2.5. Limitations of differentiating between non-expert/Expert and between generalist/specialist and combination of both distinctions of types

Both aforementioned lines of discussion have limitations that can be mitigated by combining both distinctions of types. The continuum from non-expert to expert lacks the necessary differentiation of expert and specialist within the same domain, despite the fact that specialists are an integral part of organizations (Köhler & Rausch, 2022). Hence, the individuals referred to as specialists in the organizational learning literature can be regarded as experts from the perspective of the expertise literature (see also Ericsson, 2018b, 2018b; Köhler & Rausch, 2022). In contrast, the expertise literature does not focus on the definition of a generalist; thus, it would most likely regard such an individual as a non-expert in any of the engaged domains, subdomains, or tasks (e.g., a "jack-of-all-trades"; Becker & Murphy, 1992, p. 1139; see also Dreyfus & Dreyfus, 1986, p. 20). While a generalist might still be on the developmental path to becoming an expert, the generalist/specialist distinction does not consider the developmental aspect that is inherently part of the non-expert/expert differentiation (Dreyfus & Dreyfus, 1986). Furthermore, the literature is inconsistent regarding whether generalists act within one domain or several domains and whether specialists work on one task within one domain or the whole domain (see, e.g., Teodoridis et al., 2019; Wang & Murnighan, 2013). Hence, the task bundles, the domain scope, and the competencies of generalist and specialist are too vaguely defined. Moreover, the same might be true to some extent for the non-expert/expert differentiation, as the expertise literature rarely defines the task bundles and the domain scope of experts (Köhler & Rausch, 2022).

Thus, instead of differentiating between *non-expert* and *expert* or between *generalist* and *specialist* across or within domains, we argue for differentiating between *non-expert*, *non-specialist*, *expert*, and *specialist* within each domain of an organization (e.g., controlling, sales, and so forth). This approach offsets the limitations of the two aforementioned differentiations. For instance, within sales, one employee might be an expert while others are non-experts who could develop over time into experts. Furthermore, there might be a single specialist in sales who is responsible for a certain set of tasks, such as customer complaints. These scenarios can be only partly captured by the generalist/specialist or non-expert/expert distinction.

2.6. Expertise and specialization in organizations and social networks

Altogether, we assume that experts have very high skill levels for many (but not all) relevant tasks in a domain and at least medium skill levels for the remaining tasks. Meanwhile, specialists whose specialization resulted from a division of labour have only a narrow set of highly developed skills within a domain (e.g., being solely responsible for answering customers' questions in business-to-customer sales) while having under-developed skills for most other tasks in that domain (Becker & Murphy, 1992; Wang & Murnighan, 2013). In the case of a specialist who is responsible for a whole domain (e.g., a sole lawyer in an organization), the skill profile might develop more evenly across skills, similar to that of an expert. However, this specialist's skill profile would presumably still not develop to the extent of an expert's skill profile, since the social environment for competence development (see also "expert others"; Billett, 1994, p. 4) is missing (Gruber & Harteis, 2018; Köhler & Rausch, 2022; Lave & Wenger, 1991; Tynjälä, 2013). Hence, the main characteristic of expertise is very high domain-specific competence relative to peers who are entrusted with the same tasks but have yet to reach the same competence level. Meanwhile, he main characteristic of specialization is medium or high task-specific competence in tasks with which no one else in the immediate work environment is entrusted. It is relatively simple to identify the latter type of specialist, who is responsible for a single domain, whereas it is more difficult to identify the constructs of specialization and expertise within one domain, especially if the division of labour is based on informal agreements among peers. Such informal self-organization presumably gains significance in flat hierarchies, semi-autonomous group work, and project-oriented organizations (see, e.g., Gemünden et al., 2018; Kudaravalli et al., 2017; Midler, 1995).

Within an organization's social network, an individual is more likely to be asked for advice if peers working on the same tasks perceive that individual as having high expertise (Nadler et al., 2003; Wong, 2008; see also van der Rijt et al., 2013). However, employees ask advice not only from peers with a similar skill set but also from peers with expertise in a different skill set (DiVincenzo & Mascia, 2017) in a "complementary" sense (e.g., within a project team; Lőrincz et al., 2020 −17; see also, pp. 16; −17; see also Kudaravalli et al., 2017). Hence, employees are only inclined to ask for advice if they are aware of their peers' specific expertise and specialization (Nadler et al., 2003; Nebus, 2006; see also DiVincenzo & Mascia, 2017; Treem & Leonardi, 2017). Furthermore, social networks are highly dynamic and changeable due to the involved peers' constant interaction and formation of new ties, which affect their position in the network (Nebus, 2006). Nevertheless, employees with high expertise are assumed to show high in-degree centrality and, thus, take a central position within a social network, whereas employees with high specialization take a relatively peripheral position because they are responsible for a distinct set of tasks (Becker & Murphy, 1992; Cross & Prusak, 2002; de Toni & Nonino, 2010; Grutterink et al., 2010; Jones & Kelly, 2013; Köhler & Rausch, 2022; Kudaravalli et al., 2017; Müller-Prothmann, 2006, 2007; Palonen & Hakkarainen, 2014; Wong, 2008).

Based on the considerations in this section, in Table 1 we differentiate between expertise and specialization within organizations, which to our knowledge has not previously been done with this level of detail. Our differentiation is adapted from Ackerman (2011), Becker and Murphy (1992), Chi (2006), Cross and Prusak (2002), de Toni and Nonino (2010), Ericsson (2018b, 2018b), Jacobs and Washington (2003), Jacobs and Park (2009), Köhler and Rausch (2022), Lave and Wenger (1991), Mieg (2001), Palonen and Hakkarainen (2014), Shanteau (1992), Sternberg (2005), Taylor (1911), Teodoridis et al. (2019), and Wang and Murnighan (2013).

3. Overview of studies

To address RQ1, study 1 applies social network analysis (Knoke & Yang, 2020) to examine whether being asked about work-related problems is associated with one's actual skill level or with getting more requests in general. To address RQ2, study 2 expands the social network analysis by utilizing an ERGM. To address RQ3, study 3 computes and correlates the distance between employees' actual skill profiles and hypothesized skill profiles.

4. Study 1

The purpose of study 1 is to investigate whether the in-degree centralities for each of three skill bundles relate to participants' self-assessed skill level in these skill bundles and to the in-degree centralities of the other skill bundles.

4.1. Participants

Employees working in the third-party liability and risk analysis domain of a globally operating insurance company ($N = 351$; 78% of employees in this domain) participated in the study. This knowledge-intensive domain involves creating and evaluating products for customers and handling claims by customers and third parties (see, e.g., National Center for O*Net Development, 2022). The participants were mostly middle-aged ($M = 46.9$ years, SD = 11.0) with an average tenure of $M = 10.7$ years (SD = 8.9). Of the participants, 52% were male, 48% were female, and 19% had managerial responsibilities. Communication in the organization was conducted primarily in English (for 304/32/15 individuals, the primary language was English/Spanish/German). Participation was voluntary, and all participants provided written informed consent. The ethics committee of the University of Mannheim approved the research project. Of the 351 employees, 344 (76.4% of the overall network) were ultimately considered in the analyses.

4.2. Measures

Data were obtained from three sources: a) age, gender, and tenure were retrieved from the organizational database; b) the social network was constructed through peer nominations; and c) self-assessed skills and scales on expertise and specialization were collected through self-reports. The surveys for b) and c) were based on the company's skill model, which is used to track the employees' skill profiles and development. The organization defines 29 skills in the investigated domain, of which 18 are

Table 1. Differentiation between expertise and specialization in organizations.

	Intra-domain expertise	Intra-domain specialization
Competence or skill profile in one's domain or subdomain	Very high; not all skills within a domain have to be very highly developed	Medium to high; some skills are highly developed, while most are below average
Importance of time spent in one's domain	High	Low
Perception of and relative to peers	Perceived as an expert by peers; self-perceived as an expert relative to peers	Perceived as different by peers; self-perceived as different relative to peers
Skill specificity	Low; works on same task types as peers but handles tasks at all levels of difficulty	High; works solely on a single or a few tasks
Importance of knowledge sharing/Importance of advice seeking by peers	High/High	Low/Low to medium; relatively peripheral

insurance-specific core skills (e.g., third-party liability, insurance product development, liability insurance, professional indemnity, portfolio assessment); 7 are domain-related software skills (e.g., specific contract management tool); and 4 are social skills (e.g., working in an international context which necessitates cultural sensitivity).

4.2.1. Advice seeking

Participants were requested to nominate five employees who they asked for advice in cases of work-related problems for each of the three skill bundles of core skills, software skills, and social skills ("Who do you ask for advice in case of problems regarding core skills?", "Who do you ask for advice in case of problems regarding software skills?", and "Who do you ask for advice in case of problems regarding social skills?"). To limit respondent fatigue, individuals were asked to name a maximum of five individuals for each skill bundle; however, it was possible to name the same individual for multiple skill bundles. Although it could be argued that participants might want to nominate more than five peers in a given category (Smith, 2012), in our sample only four individuals named the maximum number of five peers for a single skill bundle. According to Kossinets (2006), the response rate of 78% of the target domain's employees and 76.4% in the sample for the analyses should provide good estimates regarding network parameters. For each participant, the in-degree centrality for each of the three skill bundles was computed. An employee's in-degree centrality describes how many peers in the network nominated that employee (Knoke & Yang, 2020). In contrast, an employee's out-degree centrality describes how many peers in the network were nominated by that employee (Knoke & Yang, 2020). To protect the individual participants' anonymity, the results were shared with the participating organization only in an aggregated form (i.e., no information for single nodes, only overall results for the entire group of participants). The combined network for core, software, and social skills is shown in Appendix 1. The overall network has more evenly distributed out-degree centralities compared to in-degree centralities.

4.2.2. Self-assessed skills

Participants were asked to self-assess their competence on each of the 29 skills on a four-point Likert scale (1 = no knowledge, 2 = basic, 3 = intermediate, 4 = very high competence). To avoid overburdening the participants, we equated knowledge and competence in the questionnaire, as we assumed that participants do not significantly differentiate between these concepts.

4.2.3. Scales on expertise and specialization

Based on the characteristics of expertise and specialization presented in Table 1, we derived three items for each construct, displayed in Table 2, which the participants rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). A confirmatory factor analysis (CFA) and correlations were computed to investigate the construct validity, discriminant validity, and convergent construct validity of expertise and specialization (see supplemental analyses for details; Brown, 2015; DiStefano & Hess, 2005; Hubley, 2014; Piedmont, 2014; Rönkkö & Cho, 2022). The CFA model is acceptable with Chi-square/df ratio = 2.20 (Chi-square = 17.57, df = 8, p = .025), CFI = .982, TLI = .967, RMSEA = .059, p = .297, SRMR = .040 (Brown, 2015, pp. 72–75; Browne & Cudeck, 1993; Hoe, 2008; Hu & Bentler, 1999; Kenny et al., 2015).

4.3. Analysis

Not all participants completed all 29 skill items. Since there are no missing data regarding the self-assessment of expertise and specialization, it is assumed that data are missing for certain skills because participants only provided the relevant information. This assumption is supported by the fact that participants skipped selected items in the middle of the questionnaire, (e.g., skipping skills 15 and 16 but responding to skills 14 and 17) rather than an arbitrary block of items (e.g., the second half of the questionnaire). Only seven participants did not self-assess any of the 18 core skills. These participants' data were removed. For the remaining 344 participants retained for the following analyses, the missing items were coded as the lowest level (i.e., no knowledge).

To address RQ1, the highest self-rated skills were computed by summing a participant's highest self-rated skills for each of the three skill bundles (core skills, software skills, and social skills). The rationale for this approach is that individuals with very high skill levels are likely to receive many work-related questions from peers. For instance, if a participant rated three of the 18 core skills with a 4 (expert level), this participant would have three highest self-rated skills for skill bundle 1–18. The number of highest self-rated skills was computed to differentiate individuals who perceived themselves as highly competent in a skill bundle. In an alternative approach, we also tested summing all the second-highest self-rated skills. The rationale for this alternative approach is that individuals presumably receive work-related questions regarding a skill even if they only have an intermediate skill level. Furthermore, the in-degree centrality was calculated for each of the three skill bundles. Regarding the in-degree centrality, we inferred the complete network from the collected ego network data, an approach that has been shown not to lead to major errors (Butts, 2008b; Smith, 2012, 2015). The ego network-related

Table 2. Questionnaire items for expertise and specialization in organizations.

	Intra-domain expertise	Intra-domain specialization
Self-perception relative to peers	In my work environment I am perceived as an expert.	My typical work tasks are very different from the typical work tasks of colleagues in my work environment.
Skill specificity	In my work environment, the most difficult and demanding tasks are usually assigned to me.	In case of vacation or illness my tasks remain undone.
Importance of knowledge sharing/ Importance of advice seeking by peers	Even experienced colleagues in my work environment often ask me for professional advice.	Hardly anyone in my working environment is familiar with my specific work tasks.

responses of each participant were aggregated to portray the whole network by compiling the ego network data into one edge list for each of the skill bundles. For instance, if participants A and B both nominated participant C for advice seeking for a skill bundle, then participant C had an in-degree centrality of two in the whole network regarding this skill bundle. The in-degree centralities were computed with the R package network (Butts, 2008a) and the R package sna (Butts, 2008c). Since the data of the six ordinal variables are not normally distributed (Shapiro-Wilk values ranging from W = .332 to W = .752 with $p < .001$ for all six variables), Spearman's Rho (Bishara & Hittner, 2012; see also Myers & Sirois, 2006) was calculated with SPSS 28 to determine if a high skill level was correlated only with receiving more requests for that skill bundle or with requests for other skill bundles as well. Following Myers and Sirois (2006), the Spearman correlations were subjected to a Fisher transformation to test for significance regarding differences between correlations (Myers & Sirois, 2006; see also Zar, 2005), utilizing the R package diffcor (Blötner, 2022).

4.4. Results and discussion

The results in Table 3 show stronger Spearman correlations among most of the in-degree centralities compared to the correlation between the in-degree centrality of a given skill bundle and the self-assessment of that skill bundle (Fisher's z-test with values ranging from $z = -2.07$ to $z = -6.27$ and $p < .05$; two-sided). However, the correlations of in-degree skills 1–18 with the highest self-rated skills 1–18 and in-degree skills 19–25 are not significantly different ($z = -.709$, $p > .05$; two-sided).

If all of the second-highest (intermediate-level) self-rated skills are summed for each skill bundle, then the correlation between in-degree centrality and the number of highest self-rated skills for each of the three skill bundles vanishes, with values of .182**, .240**, and .291**. In this alternative approach, the correlations among the in-degree centralities are significantly different from the correlation between the in-degree centrality of a given skill bundle and the self-assessment regarding that skill bundle (Fisher's z-test with values ranging from $z = -4.900$ to $z = -7.496$ and $p < .05$ (two-sided)).

Hence, the results indicate that the number of advice requests regarding a particular skill bundle is, in general, more closely related to the number of advice requests in general than to one's self-assessment of that skill bundle. However, this result is not as clear for skills 1–18.

There might also be self-reinforcing processes, in that the increased visibility and peer recognition of employees who are asked for advice more frequently may encourage them to be more helpful (Nebus, 2006; Treem & Leonardi, 2017), leading them to receive advice requests regarding other skill bundles. Hence, highly skilled employees may experience a variation of the halo effect (see, e.g., van der Heijden, 2023), with high recognition regarding one skill bundle leading to high recognition across all skill bundles within a domain. However, other factors might influence this halo effect, such as personality (Gill et al., 1998), availability (Tynjälä, 2013; see also S. Kim, 2013), "perceived willingness to share advice" (Nebus, 2006, p. 615) to increase their own status within the group (Park et al., 2017), the tendency to ask the same peers for advice again (Nebus, 2006), or the tendency to ask for advice as a form of compliment (Dahling & Whitaker, 2016). In addition, "gender, education, occupation, class, and tenure" (Ridgeway, 2001 as cited in Copeland et al., 2008, p. 76), social status (Agneessens & Wittek, 2012; Lazega et al., 2012), and differences or commonalities in skill sets (DiVincenzo & Mascia, 2017; Lőrincz et al., 2020) might be confounding factors in the suggested halo effect. Additionally, the halo effect might also be explained by recall bias; that is, participants may only remember asking peers that come to mind easily (Rice et al., 2014). Finally, participants might dismiss or simply not be aware of their peers' skill levels (de Toni & Nonino, 2010; Nebus, 2006; Treem & Leonardi, 2017).

To further investigate the results of study 1, an ERGM was computed. An ERGM is an in-depth approach to network analyses that incorporates the above-mentioned social processes as well as individual and structural factors (Knoke & Yang, 2020; Lusher & Robins, 2013b). For instance, an ERGM can incorporate the social process of employees who are asked for advice more frequently due to their high skills in a particular skill bundle, thereby becoming more connected to others, more known within the domain's community, and, potentially, more often approached by peers because they are already well-known (Lusher & Robins, 2013b).

5. Study 2

The purpose of study 2 is to investigate the social processes and factors in the advice network through an ERGM.

5.1. Participants & measures

Study 2 uses the same data collected for study 1.

5.2. Analysis

For RQ2, an ERGM was computed using the R package ergm from The Statnet Project (Handcock et al., 2023; Hunter et al., 2008; Krivitsky et al., 2023). The R package ergm.ego (Handcock et al., 2023; Hunter et al., 2008; Krivitsky, 2023), the specific

Table 3. Spearman's Rho for advice seeking for work-related problems in the domain of risk analysis.

Variable	n	M	SD	1	2	3	4	5	6
1. Highest self-rated skills 1–18	344	2.15	2.92	1					
2. Highest self-rated skills 19–25	344	.31	.88	.280**	1				
3. Highest self-rated skills 26–29	344	.91	1.31	.635**	.309**	1			
4. In-degree skills 1–18	344	1.06	2.92	.496**	.217**	.358**	1		
5. In-degree skills 19–25	344	.29	.95	.275**	.398**	.252**	.532**	1	
6. In-degree skills 26–29	344	.40	1.32	.380**	.348**	.347**	.591**	.664**	1

N = 344. ** Spearman's Rho is significant at the .01 level (2-tailed). Skills 1–18 are core skills, skills 19–25 are software skills, and skills 26–29 are social skills. Number of highest self-rated skills is computed for each employee by summing all the highest self-rated skills (expert-level) within each respective skill bundle.

purpose of which is to analyse egocentrically sampled data, was not used because only a limited number of terms are currently available in the package. For a recent utilization of ERGM in organizations, see Homburg et al. (2023). For further information on ERGM, see J. Y. Kim et al. (2016) and Lusher et al. (2013). Overall, the network for the ERGM consists of 344 members with 535 directed ties between these individuals with the network-density of .0045.

In ERGM, endogenous, individual, and exogenous factors are considered regarding the formation of ties (Knoke & Yang, 2020, pp. 124–125; Lusher & Robins, 2013b), and the term *formation* is used to describe how different factors influence the establishment or lack of a tie between two nodes (Lusher & Robins, 2013b). Endogenous factors are used to describe the emergence of ties based on internal processes within the network (Lusher & Robins, 2013b). For instance, an individual with a high in-degree of centrality might get more ties simply due to already having a high in-degree centrality (Lusher & Robins, 2013b). The formation of edges, the in-degree centrality, the reciprocity, and a simple brokerage are incorporated as endogenous factors in the model. For in-degree centrality, we incorporated the in-degree centralities between 0 and 5 (94.5% of the individuals) in the final model because other models with in-degree centralities above 5 resulted in worse Akaike information criterion (AIC) values. Regarding our research question, "reciprocity" (Lusher & Robins, 2013a, pp. 42–43) would describe the tendency of employee A and employee B to ask each other for advice regarding work-related problems. A simple brokerage is incorporated through two paths (Gould & Fernandez, 1989, as cited in Jasny & Lubell, 2015, p. 38), which would indicate employee A asking employee B, the broker, who in turn would ask employee C for advice regarding work-related problems. For exogenous individual nodal attributes (Lusher & Robins, 2013b), expertise, specialization, age, tenure, gender, and the mean across skills 1–18, 19–25, and 26–29 were chosen. Furthermore, leadership responsibility is conceptualized as an environmental (Knoke & Yang, 2020, pp. 124–125) or "exogenous contextual factor", as the "formal organizational hierarchy" might influence the formation of ties (Lusher & Robins, 2013b, p. 28). Each individual attribute was investigated regarding its influence on the probability of a tie formation for each node as well as in relation to connected nodes. This relates to the "homophily principle [which] stipulates that people are attracted to similar others" (Knoke & Yang, 2020, p. 124). For instance, an apprentice might be inclined to ask someone who is slightly more knowledgeable than themselves instead of the department manager. The conceptual model can be seen in Figure 1. We followed Lomi and Palotti (2013, pp. 208–210) in using a three-step model, with the first model incorporating the "baseline dyad independence model", the second model incorporating the "endogenous network effects", and the third (full) model incorporating all chosen endogenous and exogenous effects. To compare the different models, we used the AIC, which is part of the ergm package. Furthermore, the goodness of fit was assessed (Koskinen & Snijders, 2013) based on our research aims, with a focus on optimizing the model for the degree distribution of our sample, as one "should not expect an exponential random graph model to fit all features of a network" (Robins & Lusher, 2013, pp. 184–185). Appendix 3 and appendix 4 show a reasonable fit of the final model 3 in terms of in–degree and out–degree network distribution.

5.3. Results and discussion

Table 4 shows the results for the ERGM. The baseline dyad independence model (model 1) suggests that individuals tend to ask fewer peers for advice regarding work-related problems and that employees are more likely to ask each other reciprocally for advice compared to what might be observed in a randomly formed network. The endogenous network effects model (model 2), which incorporates all chosen endogenous effects, shows the same results for the arcs and reciprocated connections in the network. However, the simple two-path brokerage does not seem to play a role. Additionally, more individuals have in-degree centrality from 0 to 5 compared to what might be observed in a randomly formed network. In the final endogenous and exogenous effects model (model 3), the simple brokerage

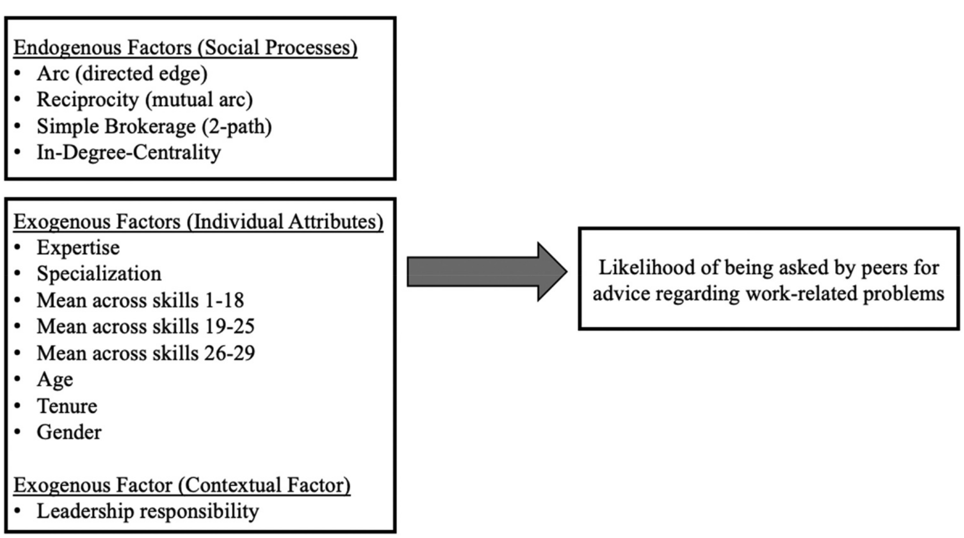

Figure 1. Conceptual model for ERGM analysis.

Table 4. ERGM estimates regarding advice seeking for work-related problems.

Parameter	Model 1 Baseline Dyad Independence Model	Model 2 Endogenous Network Effects Model	Model 3 Full Model with Endogenous and Exogenous Effects
		Estimates (SEs)	
Endogenous factor (structural social processes)			
Arc (directed edge)	−5.72 (.05)***	−3.33 (.09)***	−5.58 (.43)***
Reciprocity (mutual arcs)	3.00 (.31)***	3.38 (.36)***	2.86 (.36)***
Simple Brokerage (2-path)		−.03 (.02)	−.10 (.02)***
In-degree-centrality = 0		14.43 (.91)***	12.20 (.90)***
In-degree-centrality = 1		10.30 (.84)***	8.55 (.82)***
In-degree-centrality = 2		7.95 (.78)***	6.60 (.75)***
In-degree-centrality = 3		5.19 (.79)***	4.18 (.75)***
In-degree-centrality = 4		4.21 (.71)***	3.46 (.68)***
In-degree-centrality = 5		3.20 (.66)***	2.68 (.63)***
Exogenous factors (individual attributes)			
Expertise			.09 (.04)*
Expertise (difference)			.06 (.07)
Specialization			.03 (.04)
Specialization (difference)			.02 (.06)
Age			.00 (.00)
Age (difference)			−.00 (.01)
Tenure			.01 (.00)*
Tenure (difference)			−.03 (.01)***
Mean across skills 1–18			.30 (.07)***
Mean across skills 1–18 (difference)			−.15 (.09)
Mean across skills 19–25			.32 (.04)***
Mean across skills 19–25 (difference)			−.89 (.09)***
Mean across skills 26–29			.07 (.05)
Mean across skills 26–29 (difference)			−.10 (.08)
Gender			−.02 (.05)
Gender (similarity)			.00 (.10)
Exogenous factors (environmental structural)			
Leadership			.10 (.07)
Leadership (similarity)			.40 (.12)**
Akaike information criterion (AIC)	5426	4708	4445

N = 344. ***$p < .001$, **$p < .01$, *$p < .05$. Standard errors are shown in brackets. Skills 1–18 are core skills, skills 19–25 are software skills, and skills 26–29 are social skills.

becomes negatively significant, indicating a slight tendency to directly ask a peer who might have the answer to one's work-related problems. Additionally, expertise, tenure, the mean across skills 1–18, and the mean across skills 19–25 have a significant positive influence on the formation of ties. However, the mean across skills 1–18 and the mean across skills 19–25 have a more pronounced effect. Furthermore, the difference for tenure and the difference for the mean across skills 19–25 are negative, indicating a tendency to seek advice regarding work-related problems from peers similar to oneself. This effect is quite pronounced for the mean across skills 19–25 (software skills), indicating that individuals seek advice for work-related problems from peers who have a similar software skill level. Finally, the node match term for leadership was positive and significant, indicating a tendency to seek advice about work-related problems from peers of the same formal hierarchical position as oneself.

Expertise, the mean across the core skills, and the mean across the software skills increase the likelihood of an individual being approached for advice regarding work-related problems, which meets theoretical expectations (Köhler & Rausch, 2022; Kudaravalli et al., 2017; Lave & Wenger, 1991). However, specialization should have been negatively associated with being asked for advice. Additionally, the means across the three skill bundles are rather large categories. Hence, an individual might seek advice about a work-related problem from a peer who has, for instance, a higher mean across the core skills but a different skill set in a "complementary" sense (Lőrincz et al., 2020, pp. 16–17). Furthermore, in contrast to the core and software skills, social skills had no significant influence on the formation of ties. It is possible that the social skills are on a meta level and deeply ingrained in core and software skills; for example, being able to explain complex concepts in a comprehensible manner might increase the likelihood of being asked for advice by peers.

Expertise has only a small effect, and specialization has no significant effect, on the formation of ties. Hence, the question arises as to whether the extreme cases of expert and specialist can actually be found within a single domain through their respective, theorized skill profile or whether these two types are instead theoretical constructs that dilute in practice. Study 3 will examine this question.

6. Study 3

The purpose of study 3 is to compare participants' skill profiles to the ideal profiles of experts and specialists in the investigated domain.

6.1. Participants & measures

Study 3 uses the same data collected for study 1.

6.2. Analysis

For RQ3, hypothetical skill profiles for experts and specialists were developed (see also section 2). For experts, we assume that the skill level is very high for many skills, high for many other skills, and only mediocre for some skills while still being overall higher compared to the skill profiles of peers. Specialists within a domain instead develop very a high skill level for only a few skills, whereas they lack or have only basic knowledge of most of the other skills in the domain. These profiles are shown in Appendix 2. To compare these hypothesized skill profiles to the actual skill profiles of the participants, the skills of all participants were sorted from highest to lowest. Thereafter, distances between each participant's skill profile and presumed skill profiles were computed using the R package TraMineR (Gabadinho et al., 2011). The distances were computed through optimal matching with "automatically set" "log-state-frequencies-based indel costs" (indelslog) (Studer & Ritschard, 2014, pp. 23–24, 29). Although it is not without criticism, optimal matching with indelslog was chosen because it is a fairly balanced approach (Studer & Ritschard, 2014), as there is "no universally optimal distance index" (Studer & Ritschard, 2014, p. 1). Since the data are not normally distributed, Spearman's Rho (Bishara & Hittner, 2012) was computed with SPSS 28 to investigate the association among a participant's skill profile distance to the hypothesized skill profiles, the self-assessment for expertise and specialization, and the three in-degree centralities for each of the three skill bundles.

6.3. Results and discussion

Table 5 shows that the skill profile distance to the expert profile correlated negatively with the self-assessment of expertise and with the in-degree centrality for all three skill bundles. Hence, the higher the self-assessment of expertise, the shorter the distance from one's own skill profile to the expert profile. Furthermore, the higher the number of work-related requests from colleagues, the higher the self-assessment of expertise. Meanwhile, the results for the specialist profile are ambiguous. The in-degree centralities correlate positively with the distance to the specialist profile, but the distance to the specialist profile also correlates positively with specialization. Hence, the lower the number of work-related requests from colleagues, the higher the self-assessment of specialization. However, the higher the self-assessment of specialization, the greater the distance to the specialist profile.

Based on the theoretical assumptions (see section 2), expertise should be associated with higher in-degree centrality as well as a shorter distance to the expert profile, while specialization should be associated with lower in-degree centrality as well as a shorter distance to the specialist profile. The results support these assumptions for the expert profile, but the specialist profile deviated from our assumption, as a higher self-assessment of specialization was related to a larger distance to the hypothetical specialist profile. One reason for this might be found in our sample structure. All employees in our sample worked for the same company and in the same domain, but they were locally distributed among different branches. Therefore, the sample might contain employees who were specialists in an entire domain at their site as well as employees who were specialists, solely responsible for a few tasks in a shared domain among peers at their site (Ackerman, 2011; Becker & Murphy, 1992; Rausch et al., 2015; Wang & Murnighan, 2013). The latter case was investigated with the hypothesized specialist skill profile, which focuses on employees who are highly specialized among peers in the same domain (see also section 2).

7. General discussion

Across three studies, we investigated expertise and specialization through advice seeking within organizations. In study 1, we investigated how in-degree centrality for one skill bundle related to self-assessed skills in that skill bundle and to in-degree centrality in other skill bundles. In study 2, we investigated the social, individual, and structural factors that influence the formation of ties between peers in the examined advice-seeking network. In study 3, we investigated how in-degree centrality, self-assessed expertise, specialization, and skills relate to hypothesized skill profiles of experts and specialists.

7.1. Theoretical implications

This paper offers several theoretical contributions. First, regarding study 1, it is known that experts within a work community are asked for advice more frequently (Cross & Prusak, 2002; de Toni & Nonino, 2010; Kudaravalli et al., 2017Nadler et al., 2003; Sonnentag, 2000; van der Rijt et al., 2013) and that the availability of expert others is a crucial factor for work-related learning (Lave & Wenger, 1991; Sonnentag, 2000; Tynjälä, 2013). However, our results add to the existing body of research by demonstrating that employees within a specific domain ask the same peer for advice across different skill bundle if they have already asked that peer for advice regarding a single skill bundle.

Table 5. Spearman's Rho for employees' expertise and specialization self-assessment and distance from employees' skill profiles to hypothesized skill profiles.

Variable	n	M	SD	1	2	3	4	5	6	7
1. Expertise	344	3.59	.78	1						
2. Specialization	344	2.47	.76	.337**	1					
3. Distance to domain expert profile	344	11.86	4.69	−.362**	−.142**	1				
4. Distance to specialist profile	344	12.20	5.26	.231**	.178**	−.758**	1			
5. In-degree skills 1–18	344	1.06	2.92	.419**	.203**	−.447**	.374**	1		
6. In-degree skills 19–25	344	.29	.95	.224**	.080	−.314**	.303**	.532**	1	
7. In-degree skills 26–29	344	.40	1.32	.276**	.107*	−.423**	.392**	.591**	.664**	1

N = 344. **Spearman's Rho is significant at the .01 level (2-tailed). *Spearman's Rho is significant at the .05 level (2-tailed). Distances from one's skill profile to the hypothesized skill profiles of expert and specialist are computed with the R package TraMineRe. The in-degree skill variables describe how many peers named an individual for advice regarding the specific skill bundle. Skills 1–18 are core skills, skills 19–25 are software skills, and skills 26–29 are social skills.

Second, regarding study 2, it is known that similarity between individuals in a network is a strong driver for the formation of ties (Knoke & Yang, 2020, p. 124). This known effect was confirmed by the results, which showed that ties are more likely to form in the advice-seeking network between peers who are similar in terms of software skills, leadership, and tenure. However, this effect was not significant for core and social skills. Regarding tenure, for instance, individuals with similar tenure might have a higher chance of already knowing each other's skill sets and hence will be more likely to ask each other about work-related problems (Grutterink et al., 2010; Nebus, 2006; see also Treem & Leonardi, 2017). There is also a strong tendency of tie formation between individuals who are similar in terms of their mean software skills. The reason for this might be that individuals who are heavily involved in specific software might know each other and might even have similar problems, which they seek to solve together. This finding adds to an existing body of research suggesting that asking peers for advice is one of the most effective strategies for solving software-related problems (Leiß & Rausch, 2023a, 2023b; Leiß et al., 2022). However, we further contribute the finding that individuals specifically ask peers who have a similar skill level. Additionally, this result is amplified for the software skills because there was no significant homophily effect for core and social skills.

Third, regarding study 3, we developed ideal skill profiles as an innovative approach to identify and differentiate experts and specialists. This work adds to the existing literature on career development and knowledge management by suggesting that ideal skill profiles can be specified to look for certain individuals within organizations. However, the specialist profile needs further differentiation, as there seem to be two specialist sub-types (see also Köhler & Rausch, 2022; Rausch et al., 2015): The specialist responsible for an entire domain and the task specialist among peers within a domain. Lastly, we developed short scales on expertise and specialization that showed satisfactory reliability and validity. Overall, the differentiation of expert, non-expert, specialist, and non-specialist seems to be a fruitful theoretical distinction deserving of further research. This pragmatic distinction can be used to further the understanding of skill development and skill maintenance in the different domains within organizations.

7.2. Practical implications

It might be of interest for organizations to increase their knowledge about employees' skill sets. The short scales for expertise and specialization can be used as an additional tool to investigate and differentiate these concepts in an organization through people analytics. Doing so would increase performance and give employees the knowledge to ask the right peers about specific work-related problems (Grutterink et al., 2010; Leiß & Rausch, 2023a; Salas & Rosen, 2010; Tynjälä, 2013; see also Noe et al., 2014) – a type of knowledge that serves as an important resource for work-related learning (Leiß & Rausch, 2023a; Salas & Rosen, 2010; Tynjälä, 2013; see also Noe et al., 2014). Therefore, organizations should increase the visibility of skill profiles and differences among skill profiles (see, e.g., Competence Management Tool (CMT); Decius and Schaper (2017) to enable the right peer to be found at the right time (see also "expansive learning environments"; A. Fuller & Unwin, 2004, 2010, 2011). However, at a more subtle level, the ERGM results also suggest a tendency to seek advice regarding work-related problems from peers who have similar tenure, a similar formal hierarchical position, and especially a similar level of knowledge regarding software related skills. If advice seeking is based on factors other than expertise, valuable expert knowledge will spread less easily. Lastly, the organizational skill model could be substantiated in that individuals who rated themselves higher in the core and software skills were more likely to be asked by peers for advice regarding work-related problems.

Regarding advice seeking, knowledge sharing, and informal learning, it is important to be able to better differentiate and identify the various knowledge carriers in organizations (see also Billett, 1994; Gruber & Harteis, 2018; Lave & Wenger, 1991; Tynjälä, 2013). Organizations should introduce skill models as part of knowledge management and talent management to monitor employees' skill sets and the overall skill pool in each domain or functional area. Furthermore, differentiating these knowledge carriers might be beneficial in the context of career development within organizations – for instance, by awarding "titles" to retain valuable employees and to provide incentives for skill profile development (see also Kyndt & Baert, 2013). Additionally, if certain skill profiles can be confirmed across domains, organizations could apply these skill profiles to categorize employees to determine different needs for training by the human resources department. Furthermore, the hypothesized skill profiles could be seen as a template or ideal that employees can view as a developmental goal. However, this would necessitate a more objective evaluation of an employee's skill profile – for instance, by peers or objective performance indices linked to the different skills. Moreover, the results suggest that individuals with higher expertise, tenure, and means across core and software skills are, unsurprisingly, generally more likely to be asked for advice on work-related problems.

7.3. Limitations

Our study has several limitations. First, the developed items may not be conclusive or exhaustive for measuring employees' expertise and specialization. Second, common method variance (C. M. Fuller et al., 2016) might be a possible source of bias since expertise, specialization, and skill levels were self-assessed. For instance, in the absence of peers against whom to measure oneself, employees who are solely responsible for a single domain at a site may perceive themselves as highly skilled regardless of their actual skill level. Hence, more objective performance standards would be preferable to further assess the items' validity. However, it has been argued that common method variance might not have as significant an influence on the validity of results as often feared (C. M. Fuller et al., 2016; see also Cruz, 2022). Third, despite all the advantages of the SNA method, in-degree centralities are still based on subjective judgements that may be subject to biases (see also criticism of peer nomination; Ericsson, 2018a; cf.; Köhler & Rausch, 2022). Fourth, participants were asked to name up to five peers for each of the three skill bundles, which could result in important information being omitted if an individual wanted to name more than five peers (Smith, 2012). However, this is unlikely to be an issue in our study, as only four individuals in our sample named five peers for a single skill bundle. Additionally, it remains unclear whether recall bias (Rice et al., 2014) might be an issue. Nevertheless, the accuracy of the name generation presumably depends on, among other factors, the depth of question (e.g., "Who do you know in your organization?" vs. "Whose support can you not do without when solving your daily work tasks?") and the type of relationship (e.g., "Name all your acquaintances in your organization" vs. "Name your closest allies in your organization") (Brewer, 2000, pp. 30–31). Fifth, we utilized ego network data to infer the complete network, as complete network sampling was not possible. Although it has been shown to produce acceptable results even at low sampling percentages of 10% of the whole network, this approach is not without criticism, especially for skewed degree distributions (Smith, 2012, 2015). However, we tried to offset possible biases of missing high degree nodes by aiming for a high response rate, which was accomplished with 78% of the participating network members, of whom 76.4% were included in the analyses (Kossinets, 2006). Sixth, the data set does not contain information to control for the office arrangements of the individuals. Hence, we cannot investigate whether an individual might ask a more experienced but non-expert peer simply because that individual is nearby and willing to help. However, Treem and Leonardi (2017, p. 214) found that the "physical proximity of peers did not significantly explain success in advertising individual expertise". Furthermore, we found high correlations between in-degree centrality and expertise, as would be expected theoretically. Seventh, some methodological approaches are relatively innovative and, therefore, lack standards. For instance, the hypothetical skill profiles are theoretically grounded but could have been defined differently. Eighth, the results for RQ3 May not be transferable to another organization or even another domain, as the skill profiles are specifically related to the skill model used in the participating organization.

7.4. Future research

Regarding future research, the developed scales for expertise and specialization should be applied in various contexts and validated using additional data, such as key performance indicators or other external and more objective criteria. Furthermore, individual motivations for developing expertise or specialization should be investigated in terms of, for instance, employability (see, e.g., Decius et al., 2024). Additionally, further research should supplement the name generation with, for instance, interviews (Rice et al., 2014). For RQ1, reasons for the halo effect of a given individual being asked for advice across several skill bundles of a domain, despite being highly skilled in only one skill bundle, should be further investigated (e.g., with in-depth interviews). In addition, it might be of interest to investigate whether particular skills in the different organizational domains are crucial in determining whether someone is perceived as an expert. Hence, there should be a question for nominating peers regarding each skill compared to only skill bundles. Furthermore, the skill model of the participating organization should be further investigated; for instance, it remains unclear why social skills had no significant impact on the formation of ties. For RQ3, the different skill profiles should be investigated across domains. In particular, the specialist profile must be further investigated, since there seem to be at least two different kinds of specialists: the specialist responsible for an entire domain and the task specialist among peers within a domain. Furthermore, individuals whose skill profile is closest to the ideal expert and specialist types should be investigated regarding their self-perceived position in, and their perspective on, the social network (see, for example, Barthauer & Kauffeld, 2018).

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Data availability statement

The data that support the findings of this study are subject to strict legal restrictions and are only available through consent by the participants and the participating company. Researchers interested in the data or the participating organization's skill model should contact Daniel P. Köhler, who can forward a request to the organization.

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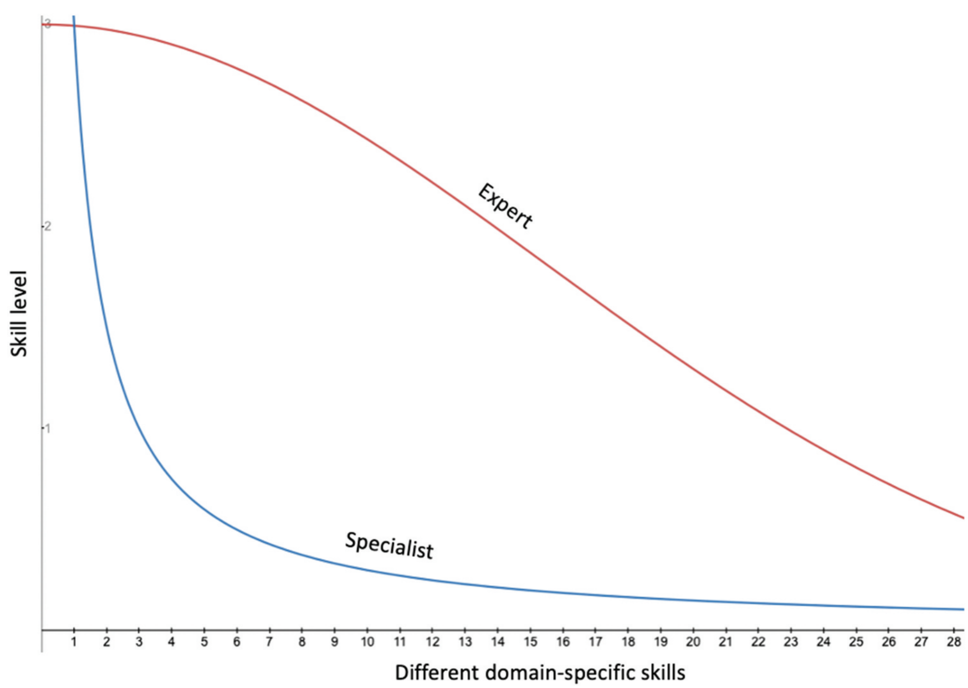
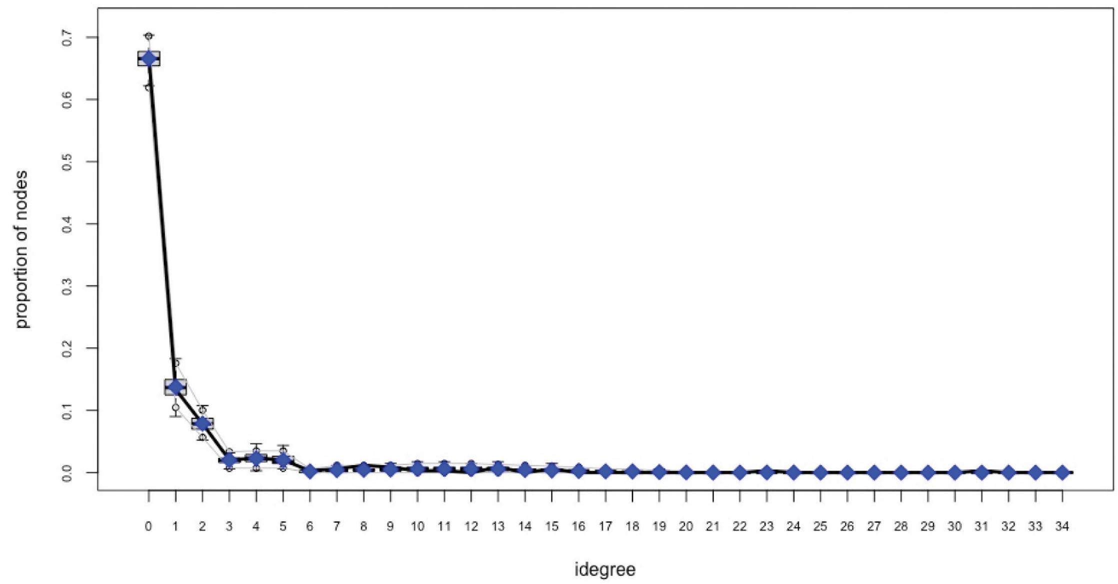
Appendices

Appendix 1. Network visualization across core, software, and social skills with a focus on 1) in-degree centrality and leadership responsibility and 2) out-degree centrality and leadership responsibility

Appendix 2. Expert and specialist profiles



Appendix 3. Goodness of fit for the final model 3 regarding the in-degree distribution of the network



Appendix 4. Goodness of fit for the final model 3 regarding the out-degree distribution of the network