https://doi.org/10.51408/issi2025_010

Network Position Matters: Collaborative Strategies, Talent Mobility, and Exploratory Innovation in Teams

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Abstract

As innovative teams increasingly depend on external knowledge, talent mobility has emerged as a crucial mechanism for acquiring novel and diversified resources that foster exploratory innovation. Despite this potential advantage, many teams fail to fully leverage newly recruited talents when these individuals lack effective network positions, resulting in underutilized innovative potential. Grounded in the complementary perspectives of collaborative networks and knowledge networks, this study investigates how newly recruited talents' positions in both collaboration and knowledge networks influence teams' exploratory innovation, and examines the interactive effects between these distinct network positions. Drawing from comprehensive data from PATSTAT and COMPUSTAT databases, we identify 65,438 cases of inter-team talent mobility and develop a robust empirical model to test our hypotheses. Our findings reveal that newly recruited talents' collaboration network centrality demonstrates an inverted U-shaped relationship with teams' exploratory innovation—moderate levels of centrality optimize innovation outcomes, while both low and excessively high centrality prove detrimental. Importantly, we discover that higher knowledge network centrality attenuates this curvilinear effect, making the inverted U-shaped curve flatter. This suggests that individuals with extensive knowledge connections maintain relatively stable innovation performance regardless of their collaboration network centrality levels. By elucidating how structural positions across different networks enable newly recruited talents to fully leverage their innovation capacity, this study contributes significant theoretical insights to our understanding of the talent mobility-team innovation link. Additionally, we provide actionable implications for managers seeking to optimize talent deployment strategies and network positioning to maximize exploratory innovation outcomes.

Introduction

As market uncertainty intensifies and innovation competition grows increasingly fierce, recruiting external talents into teams has not only become a key way to acquire novel knowledge and enhance innovative capabilities, but also an essential component of national talent attraction and development strategies (Singh & Agrawal, 2011; Agrawal, McHale, & Oettl, 2017; Wang et al., 2024). An increasing number of innovative team managers and human resources specialists are paying more attention to the relationships among talent selection, cost investment, and the resulting innovation gains. However, the extent to which successfully hired talents can actually generate innovation value for the new team remains a critical challenge for managers (Shi et al., 2023; Song, Almeida, & Wu, 2003; Tandon, Ertug, & Carnabuci, 2020).

The process of talent mobility not only involves the preliminary phases of interviews, background checks, and skills assessments to evaluate the fit between the talent and the team's needs, but also encompasses the collaboration and integration stage once newly recruited talents join the team (Jain & Huang, 2022). At this stage, newcomers must collaborate with existing technical members in the team to thoroughly understand the team's existing knowledge and R&D patterns, and subsequently contribute the novel knowledge and experience they have accumulated elsewhere (Wang & Zatzick, 2019). Therefore, if team managers wish to ensure that talent mobility truly promotes innovation, they must pay close attention to both the hiring and integration phases, recognizing that the collaboration strategies employed by newcomers after they enter the team have a direct and critical impact on team innovation.

Previous research on talent mobility has largely focused on questions such as "How to recruit suitable talents" and "How much innovation value do newly recruited talents create for the team" (Wang et al., 2024; Fahrenkopf, Guo, & Argote, 2020; Jain, 2016). Many studies investigate how the social, relational, or knowledge capital of talents influences the process of knowledge transfer (Shi et al., 2023). However, these studies have tended to overlook the integration stage of talent mobility—that is, "How can well-designed collaboration strategies help new recruits adapt to the new innovation environment". In fact, newly recruited talents can only transform their accumulated explicit or tacit knowledge from other teams into new innovative outputs after establishing effective communication and collaboration with the existing members of the new team (Acharya et al., 2022; Zhang, 2021; Myers, 2021; Wang & Zatzick, 2019).

This study focuses on the integration phase of talent mobility. For teams that rely on external knowledge to achieve exploratory innovation, the external experiences and heterogeneous technology sets brought by new talents can substantially drive breakthroughs in new fields and technologies (Song, Almeida, & Wu, 2003; Ge, Huang, & Kankanhalli, 2020; Choudhury, 2017). To elucidate the internal mechanisms by which newcomers' early-stage collaboration strategies affect teams' exploratory innovation, this study integrates network embeddedness theory and exploratory innovation theory (Yang, Lin, & Peng, 2011). This study hypothesizes that the team's exploratory innovation is influenced by these positions, given that newcomers' network locations determine both the quantity and quality of knowledge transfer, as well as the resulting differences in innovation preferences (Bunderson, Van der Vegt, & Sparrowe, 2014). Furthermore, we investigate how newcomers' positions in the knowledge network moderate the above relationship: whereas the collaboration network position reflects social capital, the knowledge network position indicates their embeddedness in terms of knowledge capital (Wang et al., 2014). Combining these two perspectives enables a more comprehensive exploration of how the integration phase of talent mobility affects exploratory innovation.

This study uses the strength of centrality to measure the quality of network positions. Specifically, this study addresses two key questions: (1) How does newcomers' collaboration network centrality in the new team influence their exploratory innovation performance within that team? (2) How does newcomers' knowledge network centrality in the new team moderate the above mechanism? We utilize global patent data from the European Patent Office's PATSTAT to identify instances of talent mobility, and then link these to the COMPUSTAT database for institutional disambiguation, ultimately obtaining 65,438 mobility records of technical talents.

Drawing on these newcomers' patent applications—both in their original and new teams—and on longitudinal patent data of the new teams, we construct measures for newcomers' collaboration network centrality, knowledge network centrality, and the team's exploratory innovation. We then employ negative binomial regression to test the proposed hypotheses.

Our empirical findings show that newcomers' centrality in the team's collaboration network exhibits an inverted U-shaped relationship with the team's exploratory innovation: at moderate levels of collaboration network centrality, newcomers can better balance the efficiency of information exchange and the costs of coordination, thus maximizing exploratory innovation; yet when centrality is either too high or too low, communication barriers, cognitive redundancy, or knowledge silos may arise, which inhibit team innovation performance. Further analyses reveal that knowledge network centrality negatively moderates this inverted U-shaped effect—when newcomers occupy higher positions in the knowledge network, the inverted U-curve becomes flatter, suggesting that individuals with rich knowledge resources maintain relatively stable innovation performance regardless of their collaboration network positions. This finding indicates that the "knowledge dimension" serves as a buffer that reduces the impact of the "collaboration dimension," enabling individuals with high knowledge network centrality to achieve consistent innovation outcomes across different collaborative contexts, while those with low knowledge network centrality are more sensitive to their collaboration network positions.

This study makes several important contributions. Theoretically, it first extends our understanding of how talent mobility influences team innovation, responding to scholarly debates regarding how external knowledge acquisition and network centrality interact to shape exploratory innovation. Second, by incorporating both collaboration networks and knowledge networks into the analysis of newcomer integration, it demonstrates that different dimensions of network centrality not only independently affect innovation but also alter the shape of the curve through interaction effects. Specifically, our findings reveal that knowledge network centrality flattens the inverted U-shaped relationship between collaboration network centrality and exploratory innovation, thus enriching our awareness of the boundary conditions of curvilinear effects under multiple variables. Moreover, this study underscores the pivotal role of individual-level network centrality in shaping team-level innovation, providing new empirical evidence for the micro–macro linkage in network theory. Practically, this study offers actionable guidance for managers in designing precise talent recruitment and integration strategies: organizations should consider newcomers' dual centrality in collaboration and knowledge networks, avoiding scenarios in which they become overly concentrated at the core, which can lead to resource redundancy or collaboration overload, as well as preventing them from being relegated to the periphery, resulting in insufficient support. Additionally, our findings suggest that firms can benefit from promoting cross-departmental collaboration and encouraging newcomers to engage extensively in various knowledge domains, thereby helping them build stronger "adhesion" in knowledge networks with broader coverage of expertise. Such approaches can help maintain stable innovation performance across different levels of collaboration network centrality and enable organizations to better leverage external talents for enhanced exploratory innovation and sustained competitive advantage.

Literature Review and Hypotheses

Talent Mobility and Teams' Exploratory Innovation

Talent mobility and its impact on teams' exploratory innovation have emerged as significant areas of research in recent years. Exploratory innovation, characterized by substantial performance improvements, cost reductions, or addressing unmet needs, often disrupts existing markets or creates new ones, distinguishing itself from incremental innovation (Bower & Christensen, 1996; Subramaniam & Youndt, 2005). Talent mobility, defined as the movement of individuals within and across organizations, facilitates the transfer of knowledge, skills, and experiences (Kogut & Zander, 1992). This process is particularly crucial in high-tech industries, where it helps bridge technological gaps and accelerates advancements (Cascio & Montealegre, 2016).

The literature consistently highlights talent mobility's role in knowledge dissemination, resource integration, and the development of innovation ecosystems (Jotabá et al., 2022). Mobile high-skilled professionals carry both tacit and explicit knowledge, providing new technological pathways and innovation inspiration to receiving organizations through learning and imitation effects (Kerr et al., 2016). Furthermore, cross-industry, cross-cultural, or interdisciplinary mobility enables the integration of diverse knowledge backgrounds and cognitive models, fostering "knowledge collision" effects (Acar, Tarakci, & Van Knippenberg, 2019).

Two core mechanisms—collaboration networks and knowledge networks—are instrumental in this process. Collaboration networks connect previously isolated innovation actors, offering teams diverse resources and technical support while enhancing their cross-disciplinary collaboration capabilities (Newman, 2001). Knowledge networks, on the other hand, accelerate knowledge flow and sharing, enabling teams to integrate diverse perspectives and foster exploratory innovations (Phelps, Heidl, & Wadhwa, 2012). The synergy between these networks not only mitigates uncertainties associated with talent mobility but also expands the boundaries of the innovation ecosystem (Eslami, Ebadi, & Schiffauerova, 2013; Deichmann et al., 2020).

To further illustrate the interplay between collaboration and knowledge networks in the context of talent mobility, we present Figure 1, which depicts four possible collaboration strategies for newly recruited talents.

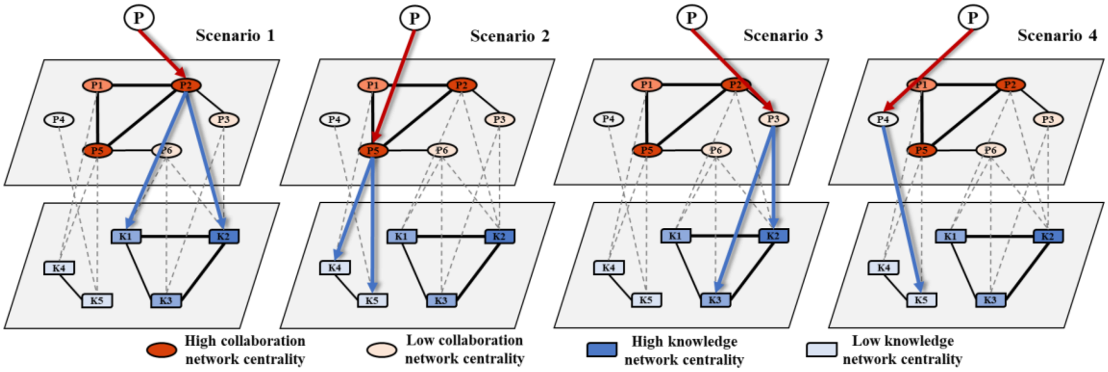


Figure 1. Schematic Diagram of Collaboration Strategies in Talent Mobility.

Figure 1 illustrates four scenarios that may arise when new talents join a team:

1) Newcomers occupy central positions in both the collaboration network and the knowledge network;
2) Newcomers are central in the collaboration network but peripheral in the knowledge network;
3) Newcomers are peripheral in the collaboration network but central in the knowledge network;
4) Newcomers occupy peripheral positions in both networks.

These scenarios highlight the complex relationship between collaboration network centrality and knowledge network centrality. While both types of centrality can contribute to innovation, their interaction may yield varied outcomes. For instance, when newcomers are central in both networks (scenario 1), they may be well-positioned to leverage their connections and expertise to drive exploratory innovation. However, this scenario might also lead to information redundancy or overload if not managed properly. Conversely, when newcomers are central in the collaboration network but peripheral in the knowledge network (scenario 2), they may facilitate information flow and resource allocation but might lack the specific expertise to substantially contribute to exploratory innovation. The opposite situation (scenario 3) could result in underutilized expertise if the newcomer's knowledge is not effectively integrated into the team's collaborative efforts.

In summary, talent mobility significantly influences exploratory innovation in teams through knowledge diffusion, team diversity enhancement, and resource reallocation. While previous research has extensively documented these effects, the specific role of network centrality in collaboration and knowledge networks during talent mobility has been underexplored. This study addresses this gap by focusing on how the centrality of newcomers in these networks impacts team exploratory innovation. The interplay between collaboration and knowledge network centrality serves as a critical mechanism in this process, facilitating knowledge transfer and organizational learning. By examining this relationship, we shed light on the complex dynamics underlying talent mobility and team innovation, offering new insights into how organizations can strategically leverage newcomers' network positions to enhance their innovative capabilities.

Collaboration Network Centrality and Teams' Exploratory Innovation

Collaboration networks, rooted in social network theory, have evolved into powerful analytical tools for understanding the structure and dynamics of scientific and organizational collaboration (Newman, 2001). These networks are characterized by nodes representing individuals or organizations, with edges signifying collaborative relationships such as co-authorship, joint projects, or advice-giving interactions (Camarinha & Afsarmanesh, 2005; Guimera et al., 2005). Key features of collaboration networks, including density, centrality, and connectivity, play crucial roles in influencing team innovation and performance (Van der Voet & Steijn, 2021). Recent research has highlighted the importance of examining the structural influence of centrality in these networks, particularly in the context of leadership and team effectiveness (Yuan & Van Knippenberg, 2022).

The relationship between collaboration network centrality and teams' exploratory innovation is complex and multifaceted, often contingent on various factors such as team size, organizational context, and the nature of the innovation tasks. Centrality, which measures a node's importance within a network, captures the extent to which an individual is connected to others and can influence information flow, resource access, and knowledge recombination (Tzabbar, Cirillo, & Breschi, 2022; Yang et al., 2021). In the context of newly recruited talents, their position in both collaboration and technological recombination networks can significantly impact their contribution to team innovation and their likelihood of remaining with the organization (Li et al., 2020).

This study proposes that the centrality of newly recruited talents within a team's collaboration network has a significant, inverted U-shaped effect on the team's exploratory innovation. This relationship can be explained through the interplay of two opposing mechanisms: knowledge integration and coordination costs. The knowledge integration mechanism positively influences exploratory innovation as centrality increases. As newly recruited talents become more central in the collaboration network, they gain greater access to diverse information, resources, and expertise within the team (Li et al., 2020; Bunderson, Van der Vegt, & Sparrowe, 2014). This enhanced access allows them to more effectively combine their unique perspectives with existing team knowledge, facilitating novel idea combinations and cross-pollination of concepts (McAdam & McClelland, 2002; Li, Mitchell, & Boyle, 2016). Conversely, the coordination costs mechanism negatively impacts exploratory innovation as centrality rises (Becker & Murphy, 1992). As newcomers become increasingly central, they face growing demands for coordination and communication with numerous team members (Srikanth & Puranam, 2014). This leads to potential information overload, increased cognitive strain, and the emergence of communication bottlenecks (Lingo, 2023). Higher centrality may lead to an imbalance in perceived power within the team. While the highly central newcomer might be more inclined to share knowledge due to their strong personal influence, other team members may experience a perceived loss of power. This can significantly reduce their willingness to share knowledge and potentially increase knowledge hiding behaviors, ultimately limiting the diversity of perspectives and ideas contributing to the innovation process (Issac et al., 2023).

The interplay of these two mechanisms creates the inverted U-shaped relationship. At low levels of centrality, the positive effects of knowledge integration are limited due to restricted access to team resources and information, while coordination costs are minimal. As centrality increases to moderate levels, the benefits of knowledge integration grow more rapidly than the coordination costs, creating an optimal balance where newcomers can effectively access and integrate diverse knowledge without being overwhelmed by excessive coordination demands. This balance maximizes their contribution to the team's exploratory innovation. However, when centrality increases beyond the optimal point, the negative effects of coordination costs begin to outweigh the positive effects of knowledge integration. The cognitive and communicative burdens of high centrality start to hinder the newcomer's ability to effectively process and utilize the wealth of information available, ultimately impeding the team's exploratory innovation performance. This inverted U-shaped relationship indicates that there is an optimal level of collaboration network centrality that maximizes exploratory innovation, where the positive effects of knowledge integration are maximized while the negative impacts of coordination costs are still manageable. Based on this, the hypotheses of this study are formulated as follows:

H1: *Newly recruited talents' collaboration network centrality exerts an inverted U-shaped effect on teams' exploratory innovation.*

Knowledge Network Centrality and Teams' Exploratory Innovation

Knowledge networks, distinct from yet interconnected with collaboration networks, play a crucial role in facilitating knowledge flow, integration, and innovation within organizations (Deichmann et al., 2020; Ren & Zhao, 2021). While collaboration networks emphasize interpersonal relationships, knowledge networks focus on the connections between knowledge elements and their dissemination processes (Phelps, Heidl, & Wadhwa, 2012). The centrality within knowledge networks reflects an individual's position in terms of access to and control over knowledge resources, which can significantly influence the dynamics of team innovation (Dong & Yang, 2016).

Building on the inverted U-shaped relationship established in the previous section, this study proposes that knowledge network centrality moderates the effect of collaboration network centrality on teams' exploratory innovation. The moderation effect can be explained by examining how knowledge network centrality influences the two underlying mechanisms - knowledge integration and coordination costs - across different levels of collaboration network centrality.

In the first phase of the inverted U-shaped relationship, where knowledge integration benefits dominate, high knowledge network centrality may attenuate the positive effect of increasing collaboration network centrality. Newly recruited talents with high knowledge network centrality already possess a rich knowledge base and extensive knowledge connections. Consequently, they may be less inclined to fully leverage the knowledge integration advantages offered by a central position in the collaboration network (Wang, Chen, & Fang, 2018). Instead, these individuals might rely more heavily on their own expertise and knowledge resources to drive innovation (Lin et al., 2022). This self-reliance can lead to a reduced need for knowledge integration from team members, potentially diminishing the marginal utility of additional collaborative connections. Moreover, high knowledge network centrality may foster greater innovation autonomy, encouraging newcomers to pursue exploratory innovation independently rather than through extensive team collaboration (Guan & Liu, 2016; Wang & Yang, 2019).

In the second phase, where coordination costs become predominant, high knowledge network centrality may mitigate the negative effects associated with excessive collaboration network centrality. Newcomers with high knowledge network centrality are likely to possess deep domain expertise, enabling them to more efficiently process and integrate information from various team members (Dong & Yang, 2016; Guan, Yan, & Zhang, 2017). This expertise can lead to more effective communication, as these individuals can quickly identify and focus on critical information, reducing unnecessary coordination efforts (Jiang, Shi, & Cheng, 2024). Furthermore, their extensive knowledge base may allow them to solve problems more independently, decreasing their reliance on other team members and thus lowering overall coordination demands (Tang, Fang, & Qualls, 2020). High knowledge network centrality may also enable newcomers to focus their innovation efforts within their areas of expertise, potentially reducing the need for cross-domain coordination and its associated costs (Wang & Zheng, 2022).

The combined effect of these moderation processes on both phases of the inverted U-shaped relationship is a flattening of the overall curve. This flattening suggests that individuals with high knowledge network centrality maintain relatively stable innovation performance across different levels of collaboration centrality. Their extensive knowledge resources and integration capabilities allow them to contribute effectively to exploratory innovation even when their collaboration network centrality is suboptimal (Guan & Liu, 2016; Wang et al., 2014). Based on this analysis, we formulate the following hypothesis:

H2: *Knowledge network centrality moderates the inverted U-shaped relationship between newly recruited talents' collaboration network centrality and teams' exploratory innovation, such that higher knowledge network centrality attenuates this curvilinear relationship—making the inverted U-shaped curve flatter.*

Overall of the Conceptual Framework

Figure 2 presents our research model, focusing on newly recruited talents and their impact on team exploratory innovation. The model illustrates the interplay between collaboration network centrality, knowledge network centrality, and innovation outcomes.

In our research context, newly recruited talents enter teams with varying degrees of centrality in both collaboration and knowledge networks. The collaboration network centrality of these newcomers has an inverted U-shaped effect on team exploratory innovation, driven by the balance between knowledge integration benefits and coordination costs. As collaboration centrality increases from low to moderate levels, knowledge integration benefits dominate, enhancing innovation. However, beyond an optimal point, coordination costs become more pronounced, leading to a decline in innovation outcomes. The knowledge network centrality of newly recruited talents moderates this inverted U-shaped relationship, attenuating its curvature. High knowledge network centrality flattens the relationship by dampening both the positive effects of knowledge integration and the negative effects of coordination costs. This suggests that individuals with high knowledge network centrality maintain relatively stable innovation performance across different levels of collaboration centrality. Our dual-network perspective integrates collaboration and knowledge dimensions, offering a comprehensive view of how talent mobility and network positions influence team innovation.

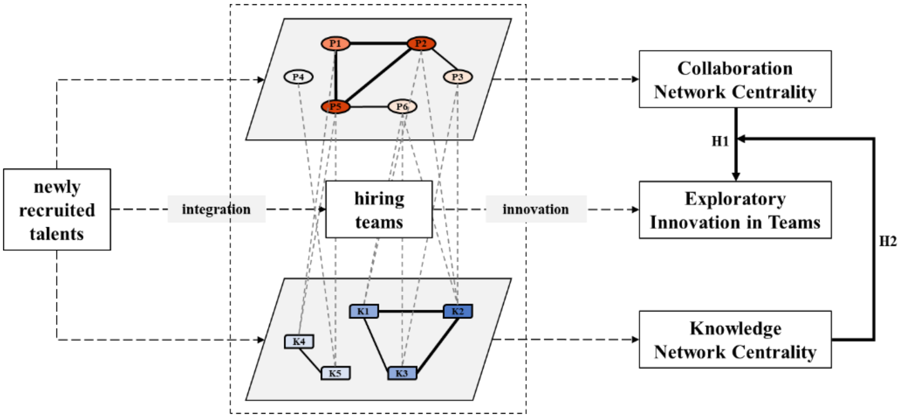


Figure 2. Research Model.

Data and Methods

Sample Selection

This study utilizes data from the European Patent Office's (EPO's) PATSTAT (2020 Spring edition), a comprehensive global patent database widely employed in innovation and patent analysis research (Wang et al., 2024; Shi et al., 2023). PATSTAT provides extensive bibliographic information on patent applications and publications worldwide since 1978. To identify talent mobility events, we track the movement of technical personnel by examining consecutive patent application records where the assignee changes, indicating a shift from one organization to another (Singh & Agrawal, 2011). Specifically, an inventor is considered to have moved when there is a change in the assignee between two successive patent applications. The midpoint between the filing dates of these two patents is used as an estimated mobility time (Song et al., 2003).

To address data ambiguities and redundancies, such as firm renaming or restructuring, we cross-reference PATSTAT data with the COMPUSTAT database, which provides detailed information on companies traded on U.S. or Canadian exchanges. Following the methodology established in prior studies (Bessen, 2008), we disambiguate firm names by matching identification fields between PATSTAT and COMPUSTAT, successfully resolving ambiguities caused by name changes, mergers, acquisitions, or parent-subsidiary relationships.

After the disambiguation process, we applied several filters to ensure the reliability and relevance of our sample. We focused on mobility events where each inventor moved only once, avoiding complications related to short observation windows and insufficient innovation data. To guarantee established collaboration networks and innovation foundations, we required inventors to have at least two patent applications in both their original and new teams. We restricted the time gap between consecutive patent applications to 2-5 years, allowing for accurate estimation of mobility timing while excluding events with potentially inaccurate identification due to short time gaps. Our study concentrated on mobility events occurring between 1996 and 2010, providing a sufficient window to observe subsequent knowledge transfer and innovation outcomes.

In addition to these primary filters, we exclude outliers to enhance data quality: inventors with an unusually large number of patent applications, those with exceptionally long technological careers (e.g., over 90 years), and those who receive an abnormally high number of citations before and after moving. These exclusions help mitigate the effects of atypical cases that could distort the analysis. After applying these stringent criteria, the final sample consists of 65,438 mobility events. This refined sample ensures that the impact of talent mobility on exploratory innovation can be accurately assessed within teams that have a pre-existing collaboration network and innovation capacity, thereby enhancing the validity and reliability of our empirical findings.

Dependent Variable

Teams' exploratory innovation measures the extent to which teams develop novel knowledge and technologies that significantly enhance performance, reduce costs, or address unmet needs. To accurately capture exploratory innovation, this study utilizes patent data co-applied by newly recruited technical personnel and their collaborators within the team.

Exploratory innovation is operationalized by analyzing patents filed within five years following a talent mobility event (t+1 to t+5 years). These patents are compared against those filed in the five years preceding the mobility event (t-1 to t-5 years) using the International Patent Classification (IPC) codes, which represent the knowledge elements within the team. A patent filed in the post-mobility period is classified as an exploratory innovation if it includes IPC codes not present in the pre-mobility period. The total frequency of these new IPC codes serves as the measure of exploratory innovation, with a higher frequency indicating a greater extent of innovative activities introduced by the newly recruited talents. To ensure the reliability and relevance of the measurements, only patents directly co-applied by the moving technical personnel and their immediate collaborators are included, ensuring that the patents reflect the direct contributions of the newly recruited talents to the team's innovation efforts.

Independent Variable

The primary independent variable in this study is collaboration network centrality (Cnc), which quantifies the position of newly recruited talents within the team's collaboration network. Cnc measures the extent to which a talent is embedded within influential and interconnected segments of the collaboration network, reflecting their ability to facilitate effective knowledge transfer and foster innovative collaborations. Specifically, Cnc is assessed by calculating the mean eigenvector centrality of all collaborators associated with the newly recruited talent over the five-year period preceding their mobility event (from t−5 to t). Eigenvector centrality is chosen for its capacity to capture not only the number of direct connections a collaborator has but also the quality and influence of those connections within the network (Dong & Yang, 2016). By averaging the eigenvector centrality scores of all collaborators, Cnc provides a comprehensive measure of a talent's overall influence and integration within the collaboration network, thereby serving as a robust indicator of their potential to drive exploratory innovation within the team. The mean eigenvector centrality for Cnc is calculated as follows:

$$Cnc_i = \frac{1}{N_i} \sum_{j=1}^{N_i} C_{ij}^{eigenvector} \quad (1)$$

Cnc_i is the collaboration network centrality of the i-th newly recruited talent. N_i is the number of direct collaborators of the i-th talent within the collaboration network. $C_{ij}^{\text{eigenvector}}$ represents the eigenvector centrality of the j-th collaborator connected to the i-th talent.

Moderator Variable

The moderator variable in this study is knowledge network centrality (Knc), which measures the position of newly recruited talents within the team's knowledge network. Similar to Cnc, Knc assesses the influence and integration of a talent within the knowledge flow processes of the team. Knc is determined by calculating the mean eigenvector centrality of all collaborators associated with the newly recruited talent in the knowledge network over the same five-year period (from t-5 to t). This measure captures the extent to which a talent is embedded within a highly influential knowledge network, facilitating efficient knowledge dissemination and integration. By averaging the eigenvector centrality scores of all knowledge collaborators, Knc serves as an indicator of the talent's ability to enhance the team's innovation capacity through effective knowledge management and integration. The mean eigenvector centrality for Knc is calculated as follows:

$$Knc_i = \frac{1}{M_i} \sum_{k=1}^{M_i} K_{ik}^{eigenvector} \quad (2)$$

Knc_i is the knowledge network centrality of the i-th newly recruited talent. M_i is the number of direct knowledge collaborators of the i-th talent within the knowledge network. $K_{ik}^{\text{eigenvector}}$ represents the eigenvector centrality of the k-th knowledge collaborator connected to the i-th talent.

Control Variables

To ensure that the effects of Cnc and Knc on teams' exploratory innovation are not confounded by other factors, this study incorporates several control variables categorized into three dimensions: characteristics of newly recruited talents, characteristics of new teams, and relational dynamics between talents and teams.

In terms of the newly recruited talents' characteristics, the study first measures the work experience of the talent. This is calculated as the number of years between the earliest patent application year of the talent and the year of their mobility event (Talent Age, Ta). A longer work age indicates greater experience, potentially enhancing the talent's ability to contribute to team innovation. Additionally, the study considers the total number of patents the talent has applied for prior to their mobility event (Talent Patent Number, Tpn). This variable serves as an indicator of the talent's accumulated technical innovation experience. The research also examines the average number of collaborators the talent has worked with on past patents before moving (Talent Social Capital Average, Tsc). This metric reflects the talent's ability to engage in collaborative innovation and leverage social networks within the team. Furthermore, the study assesses the average position of the talent in their past collaborative patents (Talent Knowledge Capital Average, Tkc). A higher average position indicates greater knowledge importance and capital, signifying the talent's influential role in collaborative endeavors.

Regarding the characteristics of new teams, the study includes a count of the number of patents the new team has filed in the five years preceding the talent mobility event (New Team Patents Base In5, Ntpb). This measures the team's existing knowledge base and innovation capacity prior to the influx of new technical personnel. Additionally, the total number of technical personnel in the new team before the mobility event is considered (New Team Talent Number, Nttn). This controls for team size and the team's experience in managing collaborations and innovation processes.

In terms of the relational dynamics between talent and team, the study incorporates a binary variable indicating whether the new team has previously cited the talent's patents in their own patents before the mobility event (Prior Cites, Pc). This captures pre-existing knowledge links that may influence collaborative strategies post-mobility. Additionally, the total number of collaborators the newly recruited talent has in the new team after the mobility event is counted (Co-inventor Count, Cic). This controls for the extent of collaborative interactions, which can directly influence the team's innovative activities. All variables and their description are shown in Table 1.

Table 1. Variables Description.

Variable	*Abbreviation*	*Description*
Dependent		
Exploratory Innovation in Teams	Exploratory	Measured by the total number of new IPC codes introduced in patents filed by the team within five years following a talent mobility event. A higher count indicates a greater extent of exploratory innovation driven by newly recruited talents.
Independent		
Collaboration Network Centrality	Cnc	Calculated as the average eigenvector centrality of all collaborators associated with the newly recruited talent over the five years preceding their mobility event. This metric reflects the talent's overall influence and integration within the collaboration network.
Moderator		
Knowledge Network Centrality	Knc	Determined by the average eigenvector centrality of all knowledge collaborators connected to the newly recruited talent over the same five-year period. It indicates the talent's position and influence within the knowledge network, facilitating effective knowledge flow and integration.
Control		
Talent Age	Ta	Calculated as the number of years between the earliest patent application year of the talent and the year of their mobility event. This measures the work experience of the newly recruited talent.
Talent Patent Number	Tpn	Represents the total number of patents the talent has applied for prior to their mobility event, indicating their accumulated technical innovation experience and expertise.
Talent Social Capital Average	Tsc	Measures the average number of collaborators the talent has worked with on past patents before moving, reflecting their ability to engage in collaborative innovation and leverage social networks within the team.
Talent Knowledge Capital Average	Tkc	Assesses the average position of the talent in their past collaborative patents. A higher average position signifies greater knowledge importance and capital, indicating the talent's influential role in collaborative endeavors.
New Team Patents Base In5	Ntpb	Counts the number of patents the new team has filed in the five years preceding the talent mobility event, serving as a measure of the team's existing knowledge base and innovation capacity prior to the influx of new technical personnel.
New Team Talent Number	Nttn	Represents the total number of technical personnel in the new team before the mobility event, controlling for team size and the team's experience in managing collaborations and innovation processes.
Prior Cites	Pc	A binary variable indicating whether the new team has previously cited the talent's patents in their own patents before the mobility event. It captures pre-existing knowledge links that may influence collaborative strategies post-mobility.
Co-inventor Count	Cic	Counts the total number of collaborators the newly recruited talent has in the new team after the mobility event, controlling for the extent of collaborative interactions that can directly influence the team's innovative activities.

Results

Descriptive Statistical Analysis of Variables

Before conducting the empirical analyses, we first present the descriptive statistics of all key variables employed in this study. This section provides the means, standard deviations (SD), correlation coefficients, and variance inflation factors (VIF) for both the focal and control variables. Table 2 contains a detailed overview of these statistics.

As shown in Table 2, the mean value of Exploratory is 81.41, with a standard deviation of 346.52. This relatively large standard deviation indicates substantial variation among teams in terms of their exploratory innovation outputs—some teams demonstrate markedly higher innovation performance due to greater resource inputs or stronger R&D capabilities, whereas others may be more constrained in these areas. Given the nature of our dependent variable, we employ a negative binomial regression model for empirical testing. This choice is justified by the characteristics of the Exploratory variable, which exhibits overdispersion. Specifically, the variance is significantly larger than the mean, indicating that a Poisson regression would not be suitable for effective empirical analysis. The negative binomial model is better equipped to handle this overdispersion, providing more accurate estimates and reducing the risk of biased standard errors that could lead to incorrect inferences about the significance of our predictors.

Regarding the key independent variables, the mean of Cnc is 0.29 (SD = 0.41), and the mean of Knc is 0.36 (SD = 0.37). These statistics suggest that newly hired talents vary considerably in how centrally they are positioned in the team's collaboration and knowledge networks—some newcomers quickly occupy more central roles, while others remain on the periphery. Examining the correlations, several notable findings align with our theoretical expectations. First, Cnc is positively and significantly correlated with Exploratory ($r = 0.10$, $p < 0.001$), indicating that a more central position in the collaboration network tends to be associated with higher levels of exploratory innovation. Cnc is also moderately and significantly correlated with Knc ($r = 0.37$, $p < 0.001$), suggesting that newcomers who occupy prominent positions in the collaboration network often hold similarly central positions in the knowledge network.

Finally, the variance inflation factor (VIF) values are generally low (all below 3), with the highest being 2.62 for Ta, well under typical cutoffs (5 or 10). Hence, multicollinearity is unlikely to pose a serious issue in our regressions. Overall, these descriptive statistics and correlations lend preliminary support to our hypotheses regarding the importance of newcomers' network positions for achieving higher levels of exploratory innovation, and they set the stage for the subsequent regression analyses.

Table 2. Correlation Analysis.

Variables	*Mean*	*SD*	*VIF*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
Exploratory	81.41	346.52	/	1.00										
Cnc	0.29	0.41	1.25	0.10***	1.00									
Knc	0.36	0.37	1.20	0.00	0.37***	1.00								
Pc	0.13	0.34	1.12	0.02***	0.03***	0.06***	1.00							
Cic	2.83	3.53	1.09	0.35***	0.12***	0.13***	0.11***	1.00						
Ta	4.23	4.28	2.62	-0.06***	-0.10***	-0.06***	-0.10***	-0.12***	1.00					
Tpn	5.61	8.38	2.45	0.02***	0.01***	0.00	0.11***	0.04***	0.25***	1.00				
Tsc	3.60	2.58	1.48	0.11***	0.11***	0.15***	0.04***	0.37***	-0.08***	0.05***	1.00			
Tkc	2.27	1.62	1.60	0.09***	0.09***	0.11***	0.02***	0.29***	-0.10***	0.01***	0.77***	1.00		
Ntpb	45.40	93.46	1.04	-0.01**	-0.22***	-0.14***	-0.04***	0.02***	0.09***	0.01*	0.02***	0.02***	1.00	
Nttn	29.95	49.35	1.25	0.05***	-0.24***	-0.14***	0.03***	0.22***	-0.01*	0.02***	0.13***	0.10***	0.55***	1.00

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Data Distribution Analysis

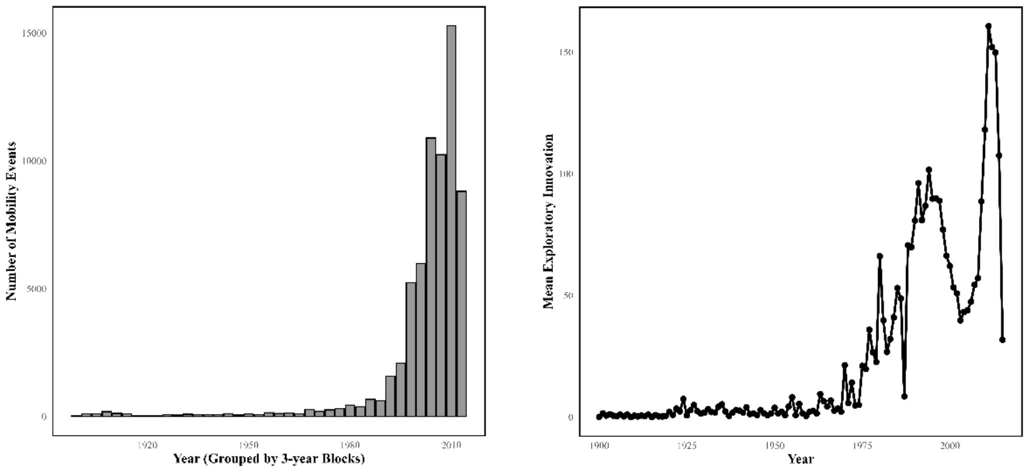
Figure 3 presents the overall distribution of the data in this study, illustrated through two subplots: (a) the number of talent mobility events within three-year intervals and (b) the average level of exploratory innovation (i.e., patent-based metric) per year. These figures help to contextualize the temporal trends in talent mobility and subsequent innovation outcomes, as well as provide preliminary insights into how broader external factors might have shaped these patterns over time.

Figure 3a displays the frequency of talent mobility events using three-year windows. The data indicate a steady rise in mobility around the early 1990s, accelerating more sharply between 2000 and 2005, followed by a peak around 2010. Several possible factors could have driven this trajectory. During the late 1990s and early 2000s, the dot-com boom and the broader emergence of high-technology industries likely fueled the demand for specialized R&D talent. As startups proliferated and established firms invested aggressively in innovation, mobility events naturally increased. The 1990s and early 2000s saw rapid globalization, with multinational corporations expanding their operations worldwide. This environment created numerous international collaborations and cross-border R&D teams, which in turn heightened the movement of technical professionals. Around the 2010 peak, firms were recovering from the financial downturn of 2008–2009 and making strategic investments in new research fields. As companies reorganized and diversified, the recruitment of external talent became a focal strategy, pushing mobility events to a high point.

Figure 3b tracks the variation in teams’ average exploratory innovation outputs across different time periods, capturing how new hires contributed to cutting-edge R&D. The figure reveals several notable fluctuations. Around 1975, there is an initial surge in exploratory patenting activities. One possible explanation is the heightened innovation impetus driven by government support and industrial restructuring post–World War II, which continued to foster both technology advancement and talent mobility. Another significant uptick occurs around 1995, potentially corresponding to the mainstream adoption of personal computing, the internet’s early commercial phase, and broader transitions in telecommunications technology. Together, these trends likely spurred new patenting opportunities and incentivized firms to acquire external talent with specialized expertise. Following the 1995 spike, a noticeable dip appears around 2000. This decline may reflect the burst of the dot-com bubble, which led to reduced R&D spending in certain sectors and a slowdown in venture funding. Consequently, the intensity of exploratory patenting could have temporarily contracted during this period of market readjustment. Subsequently, exploratory innovation spikes again from 2005 to 2010, possibly reflecting the advent of new technologies and a revitalized venture capital environment. Many firms resumed or intensified R&D investments, actively recruiting technical talents from various fields to strengthen their innovative capabilities.

Taken together, these patterns underscore both the cyclical nature of technology-driven industries and the strong link between external shocks and fluctuations in talent mobility and subsequent innovation activities. The significant peaks in mobility and exploratory innovation suggest that firms not only capitalized on buoyant markets to expand their human capital but also recognized the strategic importance of injecting novel knowledge into their existing R&D processes. Conversely, during economic downturns or after market corrections, fewer mobility events and reduced innovation outputs may indicate contraction in research investment or a more cautious approach to integrating new technological avenues.

These descriptive insights reinforce the importance of examining how newly hired talents' network positions can help—or hinder—teams in realizing exploratory innovation. As the broader historical context implies, successful talent mobility appears to depend upon both external environmental factors and the newcomers' ability to leverage their social and knowledge connections once integrated into the team.



(a) Mobility Events in 3-year Intervals (b) Average Exploratory Innovation per Year

Figure 3. Data Distribution.

Visualization of the Mobility Network

Figure 4 employs a network visualization to depict the overall pattern of talent movement across different organizations in our sample. Here, each node represents an organization, and each edge shows the aggregated number of individuals who transferred between two organizations. The resulting network is relatively sparse and dispersed, with only a few organizations standing out as central nodes—those that either attract or dispatch larger numbers of talent. These core nodes form only a handful of sub-networks, whereas most organizations remain separate from these clusters.

This dispersion suggests that talent mobility in our sample is not dominated by any single group of firms; rather, it is spread across a wide range of organizations, each with relatively distinct and independent flows of human capital. As a result, our data collection captures a more general mobility context rather than focusing on a narrow set of interconnected players. The relative sparsity of the network also provides reassurance regarding the randomness and representativeness of our sample, given that it does not overly concentrate on a small set of high-traffic channels.

Moreover, this visualization sheds light on the nature of international talent flows, revealing that even though some organizations serve as prominent "hubs," the broader pattern is one of dispersed and heterogeneous connectivity. This fragmentation reinforces the importance of understanding how new hires integrate and leverage their social and knowledge networks once they transition to a new team. Policymakers and managers interested in strengthening talent pipelines and innovation networks can draw on such insights to better design recruitment and collaboration strategies, recognizing that large-scale talent clusters are only one component of a more complex and widely distributed mobility landscape.

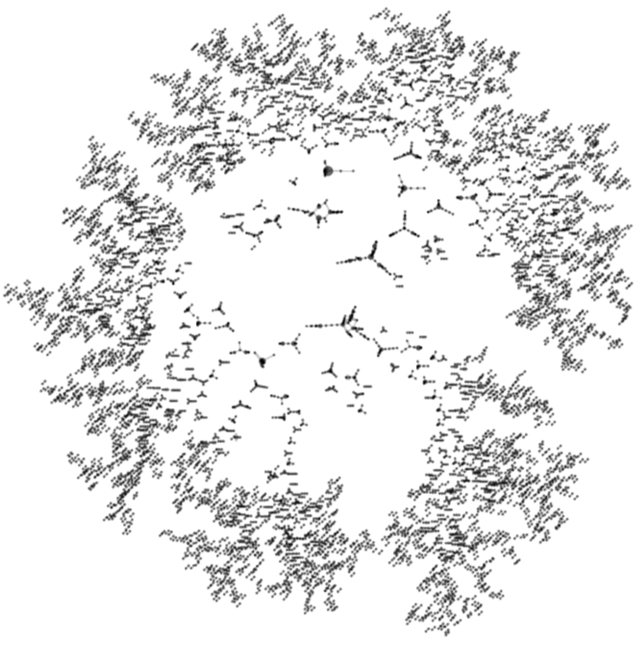


Figure 4. Mobility Network.

Network Position Correlation Relationship Analysis

Figure 5 provides a scatterplot of Cnc on the horizontal axis and Knc on the vertical axis, offering a visual representation of how these two variables co-vary across the mobility events in our dataset. Several observations stand out.

A substantial proportion of sample points fall in the upper-right quadrant of the scatterplot, suggesting that many newly recruited talents achieve both high collaboration network centrality and high knowledge network centrality within their new teams. This pattern is consistent with individuals who not only maintain active and diverse social ties but also command extensive or specialized knowledge resources. Despite the concentration in the high–high quadrant, there remain numerous cases in which newly hired talents exhibit a high level of Knc alongside a relatively low Cnc (upper-left quadrant) or a high Cnc with a relatively low Knc (lower-right quadrant). Additionally, some observations appear in the lower-left quadrant, characterized by both low collaboration and low knowledge centrality. These distributions validate our earlier conceptual typology in Figure 1, which proposed four distinct modes of newcomer integration based on the intersection of their positions in collaboration and knowledge networks. To further interpret these patterns, we draw on the mean values of Cnc and Knc to demarcate four quadrants, each reflecting a unique combination of collaboration and knowledge network positions. Assigning all sample points into these four categories helps illustrate that the hypothesized patterns of newcomer integration indeed emerge in practice and are not merely theoretical constructs.

Collectively, the distribution in Figure 5 underscores the heterogeneity of network positions occupied by newly recruited talents. While many newcomers manage to establish both broad social ties and access to rich knowledge resources, some may focus more on integrating into the knowledge structure before cultivating widespread collaboration links. This diversity of integration pathways reinforces the notion that talent mobility outcomes are shaped by a dynamic interplay between how individuals form social connections and how they leverage or contribute specialized knowledge. As our subsequent analyses will reveal, such differences in network positions can have significant implications for the level and nature of exploratory innovation within teams.

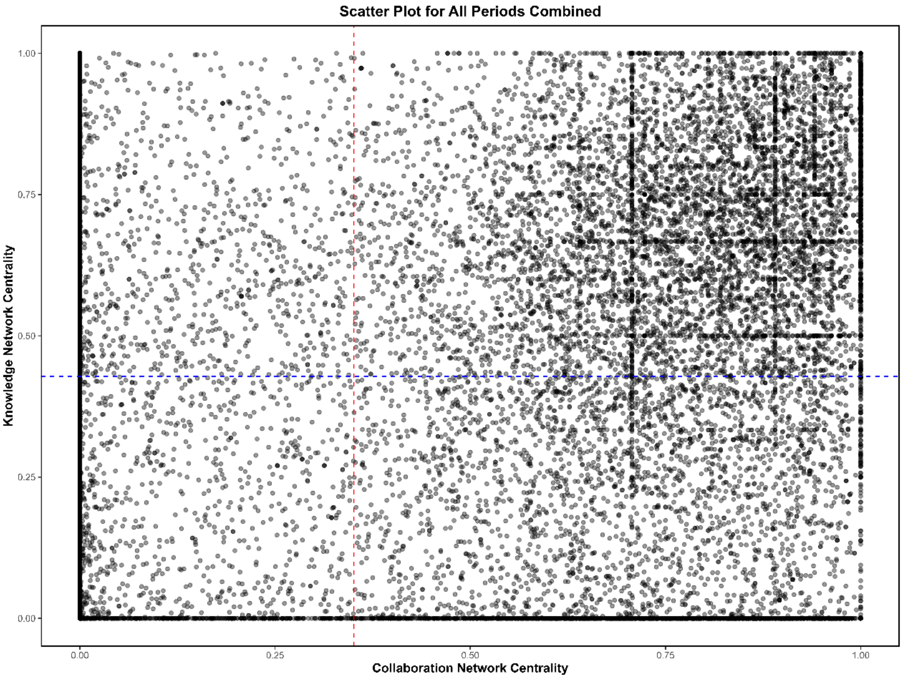
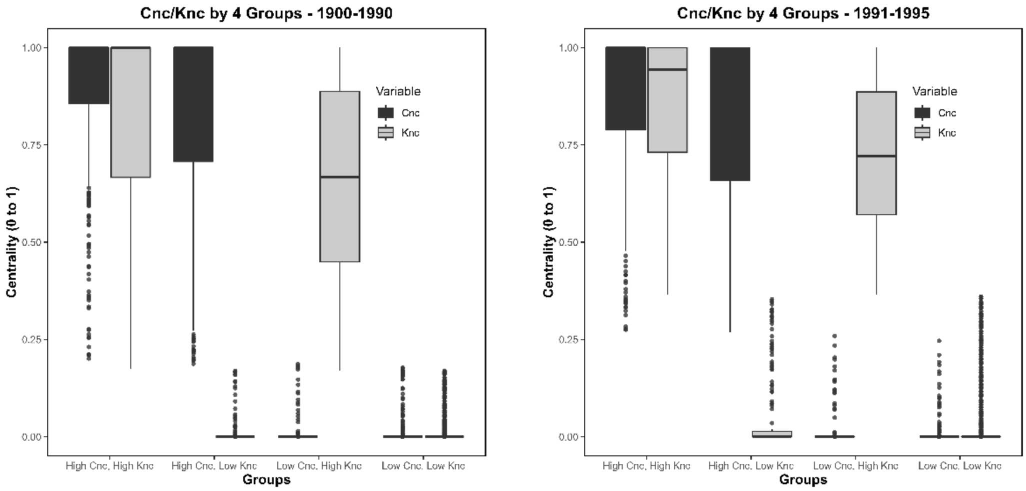


Figure 5. Scatterplot of Cnc vs. Knc.



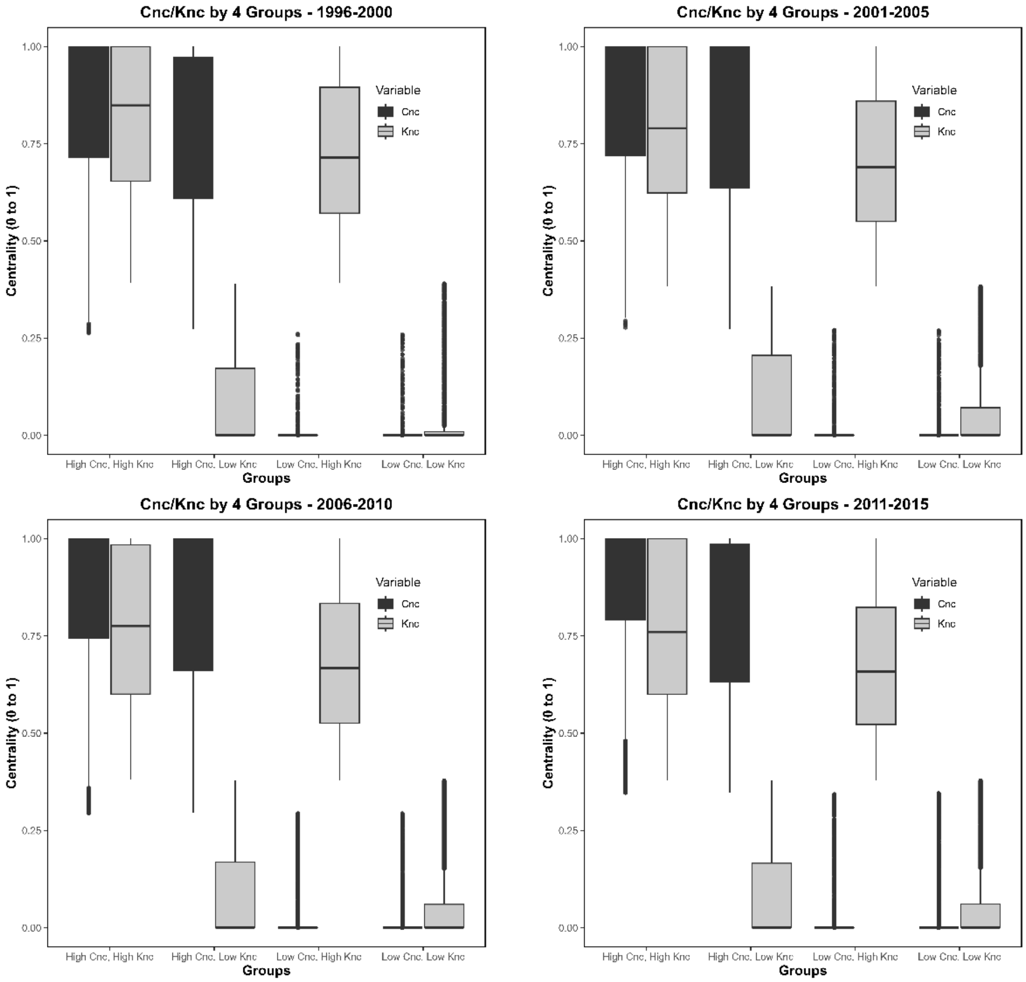


Figure 6. Boxplot of Cnc/Knc by 4 Groups.

Figure 6 extends the four-quadrant classification of newcomer integration by illustrating how these distinct categories—high–high, high–low, low–high, and low–low, in terms of Cnc and Knc—shift over time. For each of the six specified periods (1900–1990, 1991–1995, 1996–2000, 2001–2005, 2006–2010, and 2011–2015), boxplots reveal both the median and overall range of Cnc and Knc distributions within each group.

In the group of newcomers who occupy high Cnc and high Knc positions, the initial data indicate that individuals in this category consistently exhibit robust levels of both collaborative and knowledge-based embeddedness. As time progresses, however, there is a visible downward movement in the centers of both distributions, suggesting that the intensity of "double-core" embeddedness may have declined, possibly in response to more distributed organizational structures or a broader dispersion of expertise. Interestingly, in the 2011–2015 window, the central tendencies of this quadrant rebound slightly, hinting that recent waves of technology development or shifting organizational strategies may once again favor newcomers who achieve both high collaboration and high knowledge positions.

A contrasting picture emerges for those with high Cnc but low Knc. Although these newcomers initially register relatively modest knowledge centrality, the data show a gradual upward shift in their Knc values over successive periods. This movement suggests that individuals who are adept at building social connections within a team may subsequently gain or develop technical expertise, whether through training, mentoring, or project-based learning. By contrast, those with low Cnc but high Knc remain on the periphery of social collaborations throughout most timeframes, despite consistently holding a relatively strong knowledge base. Although they are not as embedded in collaboration networks as the high–high group, they still possess more specialized expertise than the low–low quadrant, pointing to a narrower, perhaps more specialized integration strategy in the team context.

The final quadrant, composed of individuals with both low Cnc and low Knc, registers a more limited capacity for either social engagement or technical contribution in the early periods of the sample. Yet after 2000, a noticeable increase appears in their median Knc values, suggesting that at least part of this group may be acquiring greater technical know-how over time. This shift could reflect a changing innovation climate, where even newcomers who start off with limited collaboration ties and knowledge resources can improve their standing if organizations provide relevant training or assign them to projects that facilitate skill development.

Taken together, these temporal boxplot patterns highlight the dynamic nature of newcomers' positions in both collaboration and knowledge networks. While some individuals maintain persistently high or low positions, the data also reveal that many evolve over time, reflecting shifts in industry priorities, organizational structures, and personal career trajectories. Understanding these trends is therefore essential for clarifying how talent mobility contributes to team-level innovation capacity, as high Cnc and Knc may be prized more strongly during certain technology cycles, whereas in other periods, the gradual elevation of knowledge among socially well-connected newcomers might become the dominant driver of exploratory R&D outcomes.

Empirical Estimation

Table 3 presents the results of the negative binomial regression models used to predict Exploratory. Model (1) includes only control variables. In Model (2), we add the key independent variable Cnc and its squared term (Cnc^2) to test the hypothesized inverted U-shaped relationship. Finally, in Model (3), we incorporate the moderating variable Knc and its interaction effects with both Cnc and Cnc^2.

The results in Model (2) provide clear evidence of an inverted U-shaped main effect. The coefficient for Cnc is 2.40 ($p < 0.01$), indicating that, up to a certain point, higher collaboration centrality is associated with greater team-level exploratory innovation. However, the coefficient for Cnc^2 is -1.60 ($p < 0.01$), suggesting that once Cnc surpasses a moderate level, its positive effect on exploratory innovation diminishes and eventually turns negative. This finding is in line with our theoretical argument that newcomers who are too central in the collaboration network may encounter communication overload or redundancy, whereas those who are too peripheral lack sufficient information exchange to drive breakthrough ideas.

To further validate the inverted U-shaped relationship, we calculated the inflection point of the curve. This inflection point (0.75) falls within the variable range of Cnc [0,1], confirming that the inverted U-shaped relationship is indeed observable within the scope of our data. The positive effect of collaboration network centrality on exploratory innovation reaches its peak when Cnc is at 0.75, after which the effect begins to decline. This finding provides strong support for our hypothesis and underscores the importance of achieving an optimal level of collaboration centrality to maximize team-level exploratory innovation. Hypothesis H1 is confirmed.

Table 3. Regression Results.

Variables	*Dependent variable: Exploratory*		
	Model 1	*Model 2*	*Model 3*
Cnc		2.40^{***} (0.10)	4.20^{***} (0.16)
Cnc^2		-1.60^{***} (0.11)	-3.10^{***} (0.18)
Knc			0.33^{***} (0.03)
Cnc×Knc			-5.00^{***} (0.29)
Cnc^2×Knc			4.50^{***} (0.30)
Pc	-0.13^{***} (0.02)	-0.12^{***} (0.02)	-0.11^{***} (0.02)
Cic	0.41^{***} (0.002)	0.38^{***} (0.002)	0.38^{***} (0.002)
Ta	-0.03^{***} (0.002)	-0.01^{***} (0.002)	-0.01^{***} (0.002)
Tpn	0.02^{***} (0.001)	0.01^{***} (0.001)	0.01^{***} (0.001)
Tsc	0.02^{***} (0.005)	0.02^{***} (0.005)	0.02^{***} (0.005)
Tkc	0.02^{***} (0.01)	0.01 (0.01)	0.01 (0.01)
Ntpb	0.0004^{***} (0.0001)	0.001^{***} (0.0001)	0.001^{***} (0.0001)
Nttn	-0.001^{***} (0.0002)	0.002^{***} (0.0002)	0.002^{***} (0.0002)
Constant	2.50^{***} (0.02)	2.10^{***} (0.02)	2.00^{***} (0.02)

The standard errors are shown in brackets, the same as below.
*, **, *** respectively represent $p < 0.1$, $p < 0.05$, $p < 0.01$

Model (3) tests the moderation effects by adding Knc and its interaction terms with Cnc and Cnc^2. Knc on its own has a significant positive effect on Exploratory (coefficient = 0.33, $p < 0.01$), illustrating that newcomers with broader or deeper knowledge connections can enhance a team's capacity for innovative outputs. More importantly, the interaction between Cnc and Knc is significantly negative (coefficient = -5.00, $p < 0.01$), and the interaction between Cnc^2 and Knc is significantly positive (coefficient = 4.50, $p < 0.01$).

These results provide support for our hypothesis regarding the moderating effect of knowledge network centrality. The positive interaction between Cnc^2 and Knc indicates that higher knowledge network centrality mitigates the negative quadratic effect of collaboration network centrality. In practical terms, these findings imply that the inverted U-shaped relationship between collaboration network centrality and exploratory innovation becomes flatter as knowledge network centrality increases. This means that for newcomers with high knowledge network centrality, the benefits of moderate collaboration network centrality are less pronounced, but the negative effects at extreme levels of collaboration centrality are also less severe.

To further illustrate this moderating effect, we have plotted the interaction in Figure 7. As shown in the figure, the inverted U-shaped relationship between collaboration network centrality and exploratory innovation becomes noticeably flatter when Knc is higher. This visual representation clearly demonstrates that as newcomers' knowledge network centrality increases, the curvilinear effect of their collaboration network centrality on team-level exploratory innovation becomes less pronounced. The graph underscores our finding that a high level of knowledge network centrality can buffer against the potential negative effects of both very low and very high collaboration network centrality, leading to a more stable relationship between collaboration centrality and exploratory innovation across different levels of Cnc.

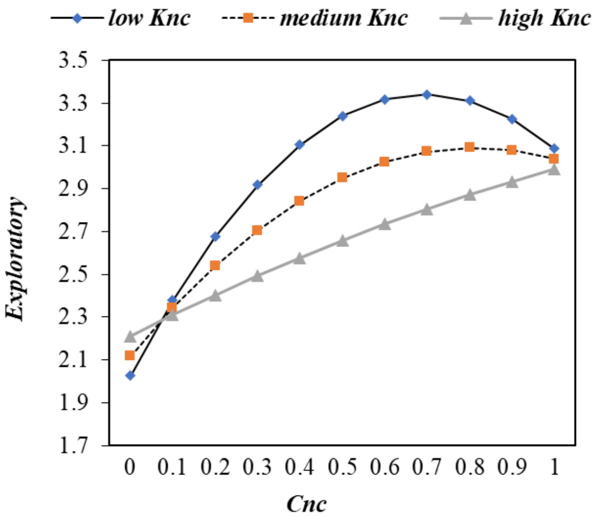


Figure 7. Moderating Effect Diagram.

Results

This study provides valuable insights into the complex dynamics of talent mobility, network centrality, and team-level exploratory innovation. Our findings contribute to both theoretical understanding and practical implications in several key areas.

Firstly, our results confirm the inverted U-shaped relationship between newcomers' collaboration network centrality and teams' exploratory innovation. This finding extends the existing literature on social networks and innovation (Newman, 2001; Li et al., 2020) by demonstrating that the benefits of network centrality are not linear but rather have an optimal point. At moderate levels of centrality, newcomers can effectively integrate diverse knowledge and resources, fostering innovation. However, excessive centrality can lead to coordination costs that outweigh these benefits, aligning with previous research on the cognitive limits of collaboration (Srikanth & Puranam, 2014; Lingo, 2023). This nuanced understanding of the centrality-innovation relationship has important implications for team composition and management in innovative organizations. It suggests that managers should strive for a balanced approach when integrating new talents, ensuring they have sufficient connections to access diverse knowledge without becoming overburdened by excessive coordination demands.

Secondly, our study reveals the significant moderating role of knowledge network centrality on the relationship between collaboration network centrality and exploratory innovation. This finding contributes to the growing body of research on the interplay between different types of networks in organizational settings (Deichmann et al., 2020; Ren & Zhao, 2021). By demonstrating that high knowledge network centrality flattens the inverted U-shaped relationship, we highlight the importance of considering both collaboration and knowledge dimensions when studying innovation dynamics. This moderation effect suggests that individuals with high knowledge network centrality can maintain relatively stable innovation performance across different levels of collaboration centrality. This finding has practical implications for talent acquisition and team formation strategies. Organizations might benefit from prioritizing individuals with high knowledge network centrality, as they appear more resilient to suboptimal positioning within collaboration networks.

Our research also contributes to the broader discussion on talent mobility and innovation ecosystems (Jotabá et al., 2022; Cascio & Montealegre, 2016). By focusing on the network positions of newly recruited talents, we provide a more nuanced understanding of how organizations can leverage talent mobility to enhance their innovative capabilities. This perspective goes beyond simply considering the transfer of knowledge and skills, emphasizing the importance of how newcomers are integrated into existing team structures.

From a practical standpoint, our findings suggest that organizations should adopt a more strategic approach to talent integration. Rather than focusing solely on an individual's expertise or collaborative skills, managers should consider how new talents can be optimally positioned within both collaboration and knowledge networks. This might involve targeted onboarding processes, mentoring programs, or strategic project assignments that help newcomers build balanced network positions. Furthermore, our research highlights the potential for using network analysis as a tool for innovation management. By mapping and analyzing collaboration and knowledge networks, organizations can identify optimal network structures and intervene to foster more effective knowledge integration and innovation processes.

In conclusion, our study provides a more comprehensive understanding of how talent mobility and network positioning influence team-level exploratory innovation. By highlighting the complex interplay between collaboration and knowledge networks, we contribute to both theoretical discussions on innovation dynamics and practical strategies for talent management in innovative organizations. Future research can build on these findings to further explore the multifaceted relationship between talent mobility, network structures, and organizational innovation.

Limitations and Future Research

While this study provides valuable insights, it is important to acknowledge its limitations and suggest directions for future research. One key limitation is the narrow scope of talent mobility scenarios examined. Future studies could expand on our findings by investigating a broader range of talent mobility contexts, such as the movement of scientists between research institutions or the transfer of management personnel across organizations. These diverse scenarios could potentially reveal richer and more nuanced innovation mechanisms that occur during talent mobility processes, contributing to a more comprehensive understanding of how different types of talent movement affect innovation dynamics in various organizational settings.

Another important area for future research lies in examining the factors that influence newcomers' evolving positions within collaboration and knowledge networks after joining a team. Future studies could focus on investigating whether and how personal characteristics, collaborative behaviors, or organizational factors affect the trajectory of a newcomer's network centrality. For instance, researchers could explore whether certain personality traits or professional backgrounds are associated with faster integration into central network positions, or how team characteristics and organizational practices influence the rate and extent of newcomers' network position changes. Such research would not only contribute to theoretical knowledge about network dynamics in organizational settings but also provide practical insights for managers seeking to optimize the integration of new talents into their teams.

Acknowledgments

This work was supported by the National Social Science Foundation of China (No. 23&ZD225) and the Data Intelligence and Cross-Innovation Laboratory of Nanjing University.

References

Acar, O. A., Tarakci, M., & Van Knippenberg, D. (2019). Creativity and innovation under constraints: A cross-disciplinary integrative review. *Journal of management*, *45*(1), 96-121.

Acharya, C., Ojha, D., Gokhale, R., & Patel, P. C. (2022). Managing information for innovation using knowledge integration capability: The role of boundary spanning objects. *International Journal of Information Management*, 62, 102438.

Agrawal, A., McHale, J., & Oettl, A. (2017). How stars matter: Recruiting and peer effects in evolutionary biology. *Research Policy*, *46*(4), 853-867.

Becker, G. S., & Murphy, K. M. (1992). The division of labor, coordination costs, and knowledge. *The Quarterly journal of economics*, *107*(4), 1137-1160.

Bessen, J. (2008). The value of US patents by owner and patent characteristics. *Research Policy*, 37(5), 932-945.

Bower, J. L., & Christensen, C. M. (1996). Disruptive technologies: Catching the wave. *The Journal of Product Innovation Management*, *1*(13), 75-76.

Bunderson, J. S., Van der Vegt, G. S., & Sparrowe, R. T. (2014). Status inertia and member replacement in role-differentiated teams. *Organization Science*, *25*(1), 57-72.

Camarinha-Matos, L. M., & Afsarmanesh, H. (2005). Collaborative networks: a new scientific discipline. *Journal of intelligent manufacturing*, *16*, 439-452.

Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. *Annual review of organizational psychology and organizational behavior*, *3*(1), 349-375.

Choudhury, P. (2017). Innovation outcomes in a distributed organization: Intrafirm mobility and access to resources. *Organization Science, 28*(2), 339-354.

Deichmann, D., Moser, C., Birkholz, J. M., Nerghes, A., Groenewegen, P., & Wang, S. (2020). Ideas with impact: How connectivity shapes idea diffusion. *Research policy*, *49*(1), 103881.

Dong, J. Q., & Yang, C. H. (2016). Being central is a double-edged sword: Knowledge network centrality and new product development in US pharmaceutical industry. *Technological Forecasting and Social Change*, *113*, 379-385.

Eslami, H., Ebadi, A., & Schiffauerova, A. (2013). Effect of collaboration network structure on knowledge creation and technological performance: the case of biotechnology in Canada. *Scientometrics*, *97*, 99-119.

Fahrenkopf, E., Guo, J., & Argote, L. (2020). Personnel mobility and organizational performance: The effects of specialist vs. generalist experience and organizational work structure. *Organization Science*, 31(6), 1601-1620.

Ge, C., Huang, K. W., & Kankanhalli, A. (2020). Platform skills and the value of new hires in the software industry. *Research Policy*, *49*(1), 103864.

Guan, J., & Liu, N. (2016). Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. *Research policy*, *45*(1), 97-112.

Guan, J., Yan, Y., & Zhang, J. J. (2017). The impact of collaboration and knowledge networks on citations. *Journal of Informetrics*, *11*(2), 407-422.

Guimera, R., Uzzi, B., Spiro, J., & Amaral, L. A. N. (2005). Team assembly mechanisms determine collaboration network structure and team performance. *Science*, *308*(5722), 697-702.

Issac, A. C., Bednall, T. C., Baral, R., Magliocca, P., & Dhir, A. (2023). The effects of expert power and referent power on knowledge sharing and knowledge hiding. *Journal of Knowledge Management*, 27(2), 383–403.

Jain, A. (2016). Learning by hiring and change to organizational knowledge: Countering obsolescence as organizations age. *Strategic Management Journal*, 37(8), 1667-1687.

Jain, A., & Huang, K. G. (2022). Learning from the Past: How Prior Experience Impacts the Value of Innovation After Scientist Relocation. *Journal of Management*, 48(3), 571–604.

Jiang, S., Shi, D., & Cheng, Y. (2024). Buyer-initiated knowledge payment facilitates free knowledge contribution in knowledge-sharing platforms: an integration of relational signaling theory and attribution theory. *Journal of Knowledge Management*, *28*(9), 2773-2792.

Jotabá, M. N., Fernandes, C. I., Gunkel, M., & Kraus, S. (2022). Innovation and human resource management: a systematic literature review. *European Journal of Innovation Management*, *25*(6), 1-18.

Kerr, S. P., Kerr, W., Özden, Ç., & Parsons, C. (2016). Global talent flows. *Journal of Economic Perspectives*, *30*(4), 83-106.

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization science*, *3*(3), 383-397.

Li, V., Mitchell, R., & Boyle, B. (2016). The divergent effects of transformational leadership on individual and team innovation. *Group & Organization Management*, *41*(1), 66-97.

Li, Y., Li, N., Li, C., & Li, J. (2020). The Boon and Bane of Creative "Stars": A Social Network Exploration of How and When Team Creativity Is (and Is Not) Driven by a Star Teammate. *Academy of Management Journal*, 63(2), 613–635.

Lin, R., Lu, Y., Zhou, C., & Li, B. (2022). Rethinking individual technological innovation: Cooperation network stability and the contingent effect of knowledge network attributes. *Journal of Business Research*, *144*, 366-376.

Lingo, E. L. (2023). Digital curation and creative brokering: Managing information overload in open organizing. *Organization Studies*, *44*(1), 105-133.

McAdam, R., & McClelland, J. (2002). Individual and team- based idea generation within innovation management: organisational and research agendas. *European Journal of Innovation Management*, *5*(2), 86-97.

Myers, C. G. (2021). Performance Benefits of Reciprocal Vicarious Learning in Teams. *Academy of Management Journal*, 64(3), 926–947.

Newman, M. E. (2001). The structure of scientific collaboration networks. *Proceedings of the national academy of sciences*, *98*(2), 404-409.

Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of management*, *38*(4), 1115-1166.

Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of management*, *38*(4), 1115-1166.

Ren, H., & Zhao, Y. (2021). Technology opportunity discovery based on constructing, evaluating, and searching knowledge networks. *Technovation*, *101*, 102196.

Shi, J., Wang, J., Kang, L., & Sun, J. (2023). How to poach the talents? Role of social capital and contextual knowledge base. *Technological Forecasting and Social Change*, 197, 122905.

Singh, J., & Agrawal, A. (2011). Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management science*, *57*(1), 129-150.

Song, J., Almeida, P., & Wu, G. (2003). Learning–by–hiring: When is mobility more likely to facilitate interfirm knowledge transfer?. *Management science*, *49*(4), 351-365.

Srikanth, K., & Puranam, P. (2014). The firm as a coordination system: Evidence from software services offshoring. *Organization science*, *25*(4), 1253-1271.

Subramaniam, M., & Youndt, M. A. (2005). The influence of intellectual capital on the types of innovative capabilities. *Academy of Management journal*, *48*(3), 450-463.

Tandon, V., Ertug, G., & Carnabuci, G. (2020). How Do Prior Ties Affect Learning by Hiring? *Journal of Management*, 46(2), 287–320.

Tang, T. (Ya), Fang, E. (Er), & Qualls, W. J. (2020). More Is Not Necessarily Better: An Absorptive Capacity Perspective on Network Effects in Open Source Software Development Communities. *MIS Quarterly*, 44(4), 1651–1678.

Tzabbar, D., Cirillo, B., & Breschi, S. (2022). The differential impact of intrafirm collaboration and technological network centrality on employees' likelihood of leaving the firm. *Organization Science*, *33*(6), 2250-2273.

Van der Voet, J., & Steijn, B. (2021). Team innovation through collaboration: How visionary leadership spurs innovation via team cohesion. *Public Management Review*, *23*(9), 1275-1294.

Wang, C., Rodan, S., Fruin, M., & Xu, X. (2014). Knowledge networks, collaboration networks, and exploratory innovation. *Academy of management journal*, *57*(2), 484-514.

Wang, J., & Yang, N. (2019). Dynamics of collaboration network community and exploratory innovation: The moderation of knowledge networks. *Scientometrics*, *121*(2), 1067-1084.

Wang, J., Shi, J., Chen, Y., Kang, L., & Sun, J. (2024). Exploring the impact of inter-organizational knowledge potential difference: an empirical investigation of inventor mobility[J]. *Scientometrics*,2024,129(12):5979–6006.

Wang, M. C., Chen, P. C., & Fang, S. C. (2018). A critical view of knowledge networks and innovation performance: The mediation role of firms' knowledge integration capability. *Journal of Business Research*, *88*, 222-233.

Wang, Q. R., & Zheng, Y. (2022). Nest without birds: Inventor mobility and the left-behind patents. *Research Policy*, 51(4), 104485.

Wang, T., & Zatzick, C. D. (2019). Human Capital Acquisition and Organizational Innovation: A Temporal Perspective. *Academy of Management Journal*, 62(1), 99–116.

Yang, H., Lin, Z., & Peng, M. W. (2011). Behind acquisitions of alliance partners: Exploratory learning and network embeddedness. *Academy of Management Journal*, *54*(5), 1069-1080.

Yang, Y., She, Y., Hong, J., & Gan, Q. (2021). The centrality and innovation performance of the quantum high-level innovation team: the moderating effect of structural holes. *Technology Analysis & Strategic Management*, *33*(11), 1332-1346.

Yuan, Y., & Van Knippenberg, D. (2022). Leader network centrality and team performance: Team size as moderator and collaboration as mediator. *Journal of Business and Psychology*, *37*(2), 283-296.

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of management review*, *27*(2), 185-203.

Zhang, G. (2021). Employee co-invention network dynamics and firm exploratory innovation: The moderation of employee co-invention network centralization and knowledge-employee network equilibrium. *Scientometrics*, 126(9), 7811–7836.