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The Impact of Dissonant Tie on Innovation Performance of Digital Transformation:
Innovation From Difficult Working Individuals

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ABSTRACT

The acquisition of innovation performance through social network relationship resources is a common behavior pattern of organizational members. Recent social network research suggests that negative ties may also have a positive impact on organizational innovation compared with positive ties. Based on this, the paper investigates the impact of dissonant tie, which are a combination of problem-solving tie and difficult working tie, on organizational innovation. The empirical results show that dissonant tie promotes organizational innovation performance and are enhanced by digital sensing and digital seizing, while the increasing effect of the dissonant tie on organizational innovation performance is not verified under the moderating effect of digital reconfiguring. The findings are useful for understanding why certain negative ties may promote organizational innovation and performance, and to provide a theoretical basis for how manufacturing companies can use complex social network ties to survive organizational change and enhance organizational adaptability in digital transformation.

KEYWORDS

Difficult Working Tie, Digital Transformation, Digital Transformation Capability, Innovation Performance, Organizational Innovation, Problem-Solving Tie

INTRODUCTION

Organizational innovation is an inexhaustible driving force for business development (Pizzi et al., 2021). Digital technology has been critical in reaching business goals, leading to innovation products, services, processes, and business models (Cloos & Mohr, 2022). At present, a new round of technological revolution and industrial change is flourishing (Rodrigues et al., 2022). Big data, cloud computing, and artificial intelligence are representative of a new generation of digital technology to accelerate the penetration of the main modes of operation of human life. Organizational innovation has brought profound change to economic and social development in a deep digital era (Busulwa et al., 2022).

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Scholars in the field of innovation also emphasize the influence of social-network ties on the innovativeness of companies (Basov, 2020). According to social-ledger theory, there are both positive and negative ties in the organizational environment. Previous studies have suggested that positive ties in social networks (e.g., opinion seeking, knowledge transfer, trust, or friendship) enable individuals to benefit from professional networks and are a benefit for innovation capability (Alshareef et al., 2020). Conversely, negative ties may contain aversive, avoidant, hostile, or difficult working relationships that burden individuals and negatively influence organizational innovation (Lai et al., 2020). However, recent research on work relationships points to the possibility of friendly relationships between individuals and their competitors, ambivalent relationships between friends and foes, or even conflicting relationships between colleagues seeking advice, considered a phenomenon of dissonant ties (Brennecke, 2020). More importantly, due to the rise of emerging technologies such as big data, cloud technology, and artificial intelligence, industrial businesses are struggling with digital transformation, and a large body of research in the innovation field has begun to consider the role of digital transformation in the organizational innovation process (Stornelli et al., 2021). It also considers the impact of digital transformation on innovation output through networking resources (Leon et al., 2020). Recent studies suggest that three core capabilities of digital transformation capability (DTC)—digital sensing, digital seizing, and digital reconfiguring—may have different impacts on organizational innovation performance (Ghosh et al., 2022). Therefore, exploring the relationship between positive and negative ties and organizational innovation and clarifying the impact of dissonant ties on organizational innovation under different DTCs has become a critical issue.

In regard to existing studies on the relationship between positive and negative ties and organizational innovation (Yang et al., 2020), although the studies have considered the new position of multiple ties in the organizational-innovation process and studied the innovation performance in different contexts (Llopis et al., 2021), there are still some general gaps. First, the combined impact of positive-negative ties in networks is not clear. Existing studies have recognized the need for positive and negative ties, but the combined effects of whether positive and negative ties can occur simultaneously in the same individual and the effects that positive and negative ties can have on the allocation of organizational resources, knowledge acquisition, and orderly operation have not been verified. Second, there are contradictory views on the impact of positive-negative ties on organizational innovation. Most previous studies have concluded that positive ties have a facilitating effect on innovation performance and negative ties necessarily have an inhibiting effect on innovation performance (Mitze & Strotebeck, 2019; Rajalo & Vadi, 2021). However, negative and positive ties may coexist and act in combination to influence innovation performance: cognitive-emotional difficult ties and problem-seeking positive ties may exist in the same individual and positively influence organizational innovation in the process of tie building. Third, a research framework on ties and organizational innovation in the context of digital transformation has not been established. The emerging technology DTC environment is bound to influence the process and outcome of organizational innovation (Baden-Fuller & Teece, 2020; Cloos & Mohr, 2022). The different opportunities for organizational innovation brought by positive-negative ties under DTC become a key issue for research in the organizational innovation field.

The rest of this study is organized as follows: first, we review the relevant literature and describe the conceptual model for dissonant ties and innovation. We then discuss the study design, including measurement and data collection. Subsequently, we discuss the results from the empirical analysis and moderating of digital transformation of dissonant ties and innovation. Finally, the conclusion summarizes our findings and discusses implications, limitations, and directions for future research.

LITERATURE REVIEW AND HYPOTHESIS SETTING

Dissonant Ties and Innovation Performance

By simultaneously studying the duality of positive and negative networks, social-ledger theory typically assumes that individual positive and negative network ties are mutually exclusive and independent and do not connect directly to the same individual. Accordingly, many scholars who study positive and negative network ties consider them as two ends of a continuum, e.g., friends versus foes (Daud et al., 2020) and supportive versus antagonistic (Barrett et al., 2021). However, based on cognitive-dissonance theory (Festinger, 1957), there may be both negative and positive ties between two individuals: the problem-solving tie, as positively constituted, can be described as a professional-network tie (Ren et al., 2021).This reflects a favorable evaluation of helping others and solving work-related problems or opportunities (Yang et al., 2020). From a value-added perspective, they are "the result of cognitive judgments that combine previous experiences, social cues, observations, and perceptions of potential contact into a whole". Problem-solving ties combine the knowledge and ideas of different individuals and add innovative value to individuals and organizations (Rodan & Galunic, 2004; Pizzi et al., 2021). Unlike other task-associated help-seeking formations (e.g., asking for advice or feedback) (Hornstra et al., 2022), problem-solving ties relate to the occurrence and evolution of nonprocedural aspects of work and organizational innovation. Individuals with these ties typically engage in intense dialogue and high levels of cognitive engagement and knowledge creation (Leon et al., 2020), which drives their co-learning and co-development. As an inherent part of knowledge-intensive work, seeking problem-solving help motivates individuals to be able to cope with more complex tasks (Wang & Lu, 2021). At the same time, a professional tie allows colleagues to exchange work-related resources and support and to actively participate in organizational innovation initiatives that are inherently task-based but generally lack emotion (Walton-Roberts, 2008). In contrast, individual network ties are emotion-based ties, such as friendship, hostility, and disgust (Mitze & Strotebeck, 2019; Santoro et al., 2020).

Thus, the second component of positive-negative ties, difficult-working ties, is a special type of negative tie and is based on the emotional ties of individual networks. Negative ties are defined as inter-individual attitudes that represent a persistent and recurring pattern of negative judgments, feelings, and behavioral intentions toward another person (Ahmad & Barner-Rasmussen, 2019; Ahn et al., 2021). It usually involves feelings of conflict, jealousy, or rejection (Can & Alatas, 2019) or has harmful work-related consequences (Battilani et al., 2018). Similar to positive network ties, different types of negative ties exist, and as Labianca and Brass (2006) highlight, they may be emotional, behavioral, or cognitive.

Overall, problem-solving as well as difficult-to-work-with ties have something in common: both can simultaneously evoke cognitive patterns and bring about organizational innovation in accordance with other individual work-related traits (Fiske & Taylor, 2008; Von Hippel & Cann, 2020), thus influencing people's individual behavior through cognitive patterns. At the same time, cognitive conflicts are also evoked: a good evaluation of another person's problem-solving ability attracts individuals toward them, yet finding it difficult to work together drives them away. Nevertheless, the two types of ties may overlap. Based on cognitive-dissonance theory (Festinger, 1957), the term dissonant tie was introduced to describe this multiplicity of positive and negative ties characterized by conflicting perceptions between individuals (Brennecke, 2020). Thus, dissonant ties include both associative and dissociative forces. Consistent with cognitive-dissonance theory, dissonant ties can be seen as counter-attitudinal behavior; they are formed when individuals have conflicting cognitive attitudes (Du et al., 2019).

More importantly, innovative performance is most likely the product of achieving multiple possible solutions and solution paths to complex, poorly structured tasks through the application of creative and analytical thinking (Chen et al., 2017). Especially in knowledge-intensive firms, efficient employees are required to provide constructive criticism and prompt new perspectives through problem-solving interactions, thereby enhancing the innovation capabilities of assistance seekers to form their solutions to complex tasks (Rodan & Galunic, 2004) and enhance organizational innovation performance (Zhong et al., 2021).

In knowledge-intensive firms, efficient employees can arrive at solutions despite the many constraints (e.g., time, money, cost, product-characteristic, or service-characteristic constraints) that may exist to accomplish the task itself (Tompson et al., 2020). Specifically, to find a solution, knowledge-intensive employees habitually seek assistance through professional-network ties. Consistent with social-ledger theory, positive networks generated with those who provide assistance inevitably lead to performance gains and enhance organizational innovation. Conversely, difficult-working ties such as negative network relationships that result in psychological burdens for the connector (e.g., reduced existing psychological security) (Santoro et al., 2020) clearly have a negative impact on organizational innovation performance (Zhang et al., 2019; Baldwin et al., 1997).

However, positive-negative ties sometimes do not exist in isolation across individuals, and, based on social-ledger theory, scholars usually assume that the effect of positive- and negative-tie multiplicity on performance is additionally interactive (Abbas & Sağsan, 2019). That is, the costs and benefits of the two types of ties are bound to cancel each other out, and the effect of dissonant ties on performance is assumed to be neutral (Zhang et al., 2022). However, based on merging social-ledger theory and multiple-network perspectives, we have recently found that dissonant ties consisting of positive-negative ties that coexist among individuals may overlap and positive and negative network ties may each have different effects rather than simply neutral impacts. From a synergistic interaction perspective, we argue that dissonant ties seeking problem-solving assistance from difficult colleagues can provide three benefits for enhancing innovation performance in knowledge-intensive organizations: first, the use of dissonant ties as network behaviors can provide opportunities for unique resources. Specifically, it allows for the adoption and benefits of rare problem-solving skills or heterogeneous knowledge from difficult colleagues. This is consistent with research findings on the tendency of individuals to seek help, i.e., people typically ask for advice from people they know better to approach, and thus asking for special resources from people they do not approach well (Xiong & Xia, 2020). This study also validates that employees' frequent mutual support with difficult colleagues leads to greater innovation. Although proximity to difficult colleagues is risky, investing the time and mental resources required to cope with potential distress enhances employees' emotional resilience (Yi et al., 2020), and relying on dysfunctional relationships for assistance can gain a special competitive advantage. In turn, by acquiring competencies and knowledge that are not widely used by other colleagues and combining them with their own knowledge, they can increase the likelihood of building solutions for their complex tasks and enhance organizational innovation performance.

Second, because the impact of dissonant ties on innovation-performance gains sometimes does not come from colleagues who are generally perceived as difficult to get along with, dissonant ties can also have knowledge heterogeneity due to interpersonal differences (Robins et al., 2009; Walkowiak, 2021) and can still contribute to innovation performance. Specifically, a second reason for employees involved in knowledge-intensive work to consciously seek problem-solving help from difficult colleagues is the desire to have their perspectives challenged. Difficult working relationships can cause individuals to question or oppose the established viewpoints of others. Thus, dissonant ties imply confrontation with disagreements and different perspectives that the person seeking assistance has never considered before. These factors are associated with creative divergent thinking and expansion of focus (Alhusen et al., 2021), and they may lead to reflexive organizational reengineering (Borrás & Laatsit, 2019), transformation of established problem concepts, and discovery of new ties between perspectives, thus allowing alternative identification and creative-solution generation. Marineau et al. (2018) provide evidence that individuals deliberately use this network behavior and succeed at work. Their research demonstrates that employees seeking advice from colleagues with whom they have task conflicts can prevent groupthink (Janis, 1972) and establishes a link to creative performance.

In summary, employees consciously seek problem-solving help from difficult colleagues, looking to them for unique resources and challenges to their own perspectives. Moreover, since dissonant ties are characterized by cognitive dissonance, this can lead to emotional distress or perceived unpleasantness (Festinger, 1957) and shift the attention of members on both ends of the tie from co-generating problem solutions to engaging in coping strategies (You & Yi, 2021), thereby enhancing organizational innovation. More importantly, dissonant attitudes can enhance the intensity of information processing (Brennecke, 2020) while leading individuals to discover new solutions (Stornelli et al., 2021; Zhou et al., 2020). The occurrence of tension between positive and negative cognitions when approaching a difficult colleague for help can also serve as a cognitive catalyst for employees to find solutions to complex tasks. Through these three mechanisms—using the unique resources of dissonant ties, the challenge of perspective, and the cognitive catalyst—the multiplicity of positive and negative relationships of dissonant ties based on synergistic interactions of cognition can bring new opportunities for innovative performance. As a result, dissonant ties are believed to contribute to the improvement of organizational innovation performance. Thus, we propose the following hypothesis:

H_1: There is a positive relationship between dissonant ties and innovation performance.

The Moderating of Digital-Transformation Capability

In recent years, many studies have emerged around the phenomenon of digital transformation. Sousa-Zomer et al. (2020) proposed three digital-transformation competencies related to organizational culture: digital skills, digital intensity, and digital-interaction conditions. Similarly, Tuukkanen et al. (2022) proposed core foundational competencies related to organizational culture for digital-culture transformation in digital transformation. Singh et al. (2021) studied the issue of inadequate capabilities and resources in small and medium-size enterprises (SMEs) and identified social-network capabilities as the main driver of digital transformation. Some researchers, such as Nwankpa and Roumani (2016) and Rijswijk et al. (2021), emphasize the role of information technology (IT) capabilities and argue that IT capabilities and relational resources are core competencies that drive firm performance, while digital-transformation initiatives are a mediator. Warner and Wäger (2019) identify a set of digital-sensing, digital-extraction, and digital-transformation capabilities in traditional industries and examined their impact on organizational innovation. Based on Teece's (2009) theoretical framework on dynamic capability, we consider digital transformation capability as a process of sensing, seizing, and reconfiguring corporate resources. As Baden-Fuller and Teece (2020) point out, such a process requires the top-management team of an organization to be innovative and adapt to a rapidly changing environment (Scupola & Mergel, 2022). In line with Teece's view, the industrial internet of things and emerging technologies have created a rapidly evolving environment that severely disrupts existing company activities and capabilities. This unstable scenario disrupts the industrial enterprise and makes traditional change solutions no longer the answer. Therefore, we need more unusual ties in social networks to adapt to the changing environment and to promote organizational innovation and development. This paper, based on Ghosh et al.'s (2022) study on the digital transformation of industrial businesses, argues that DTC consists of digital sensing, seizing, and reconfiguring and plays a positive moderating role in the impact of dissonant ties on organizational innovation performance.

The Moderating of Digital Sensing and Digital Seizing

Strategic sensing is considered a core capability in digital transformation and is widely studied by innovation scholars in the context of the industrial internet of things and emerging technologies (Scupola & Mergel, 2022). Sensing is one of the central and necessary factors in the process of digital transformation of industrial companies driven by emerging technologies and digitalization (Apilioğulları, 2022). As technology-led businesses continue to grow, it is essential for industrial companies to sense their internal and external environments and to identify digital opportunities (Zhu et al., 2021). The ability to sense digital transformation, sense the internal and external environment, and explore digital opportunities is critical to the ability to digitally transform (Zhang et al., 2022). The heterogeneous resources, questionable perspectives, and catalytic effect on innovation that dissonant ties, as cognitive and affective inconsistent ties among members, can provide in member collaboration may be exactly the elements needed in digital transformation of industrial companies to expand the space for organizational innovation (Simms et al., 2021). Thus, digital sensing can facilitate the positive impact of dissonant ties on innovation performance.

On the other hand, rapid-prototyping capability as well as seizing sensed opportunities have been recognized as core capabilities in the digital transformation of enterprises (Xiong et al., 2021). It can be said that rapid-prototyping capability is a prerequisite for digital seizing. Rapid-prototyping capabilities can enable companies to seize opportunities, drive digital transformation, and gain competitive advantage (Walkowiak, 2021). In the context of rapid prototyping to seize digital opportunities, there is a greater need for enterprise members to gain innovation performance through dissonant ties, as rapid-prototyping information usually comes from formal members (Tangi et al., 2021). In addition, evolving organizational structures need to adapt to the digital transformation of industrial firms and are more likely to motivate members to collaborate across teams and seek difficult solutions (Simmonds et al., 2021). Developing organizational structures need to adapt to the digital transformation of industrial firms and are more likely to motivate organizational members to collaborate across teams and seek out difficult ties for heterogeneous collaboration, thereby promoting innovative organizational performance (Pizzi et al., 2021).

Hence, we hypothesized the following:

H_2: Digital sensing and digital seizing positively moderate the relationship between dissonant ties and innovation performance.

The Moderating of Digital Reconfiguring

Based on dynamic-capability theory, reconfiguration capabilities are another key capability for digital transfer (Matarazzo et al., 2021). Among other things, there are two different ways in which reconfiguration capabilities can affect social networks and innovation performance. The first is that in an emerging firm, managers can create a new business model through digital transfer and thus increase the impact of dissonant ties on innovation performance. Leon et al. (2020) argues that business-model innovation influences digital transformation and that emerging technologies have a direct impact on business-model innovation.

The process of digitization generates new value creation (Tuukkanen et al., 2022), value delivery, and value-capture capabilities, new servitization, and new platform business models and digital customers. Effective organizational routines and processes become the key to digital transformation in the process of business-model change (Von Delft & Zhao, 2020). The dissonant tie, consisting of a problem-solving tie and a difficult-working tie, is likely to survive the digital transformation of industrial companies through heterogeneous knowledge and relationship resources in the process of business-model change (Rodrigues et al., 2022), and the dissonant tie may help industrial enterprises to survive digital transformation during the process of business-model change and to obtain organizational innovation performance with more organizational flexibility.

On the other hand, many studies point out that as a cultural transformation, a change in mindset is an important factor for digital-transformation capability (Lee et al., 2021; Rodrigues et al., 2022). Industrial managers need to change their mindset to achieve a favorable outcome and ease the implementation of digital transformation. Sometimes managers are simultaneously multi-threading multiple different businesses, which may involve different aspects of product development, production and sales, and seeking solutions (Cloos & Mohr, 2022; Leon et al., 2020). In this case, there is a greater need for cross-team social-network collaboration and the search for heterogeneous resources, as well as the need for opposing views to optimize problem-solving solutions, thereby enhancing organizational adaptation and organizational innovation (Ostmeier & Strobel, 2022). Thus, we hypothesize that digital reconfiguring can positively regulate the relationship of dissonant ties and innovation performance through business-model transformation and cultural transformation. Fig. 1 shows the conceptual model. Hence, we hypothesized the following:

H_3: Digital reconfiguring positively moderates the relationship between dissonant ties and innovation performance.

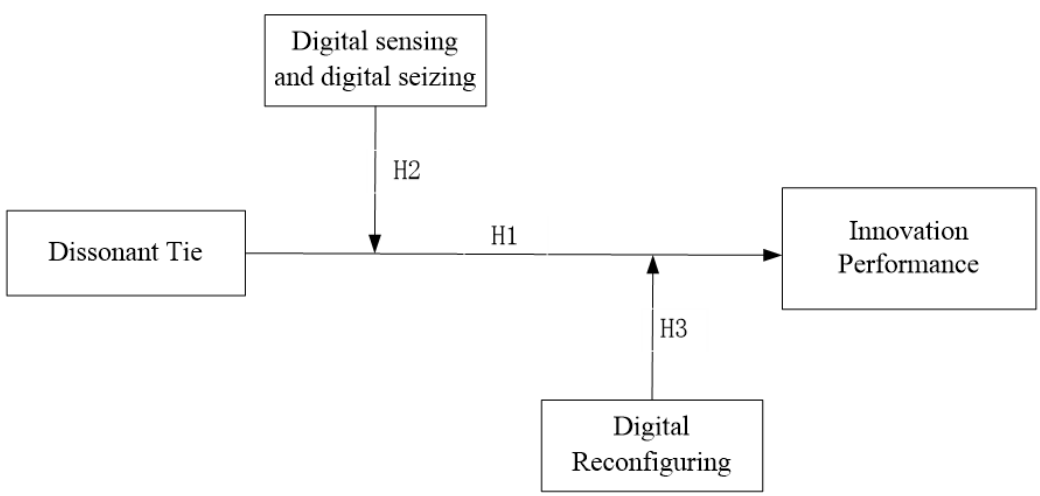
METHODOLOGY AND DATA

Sample and Data Collection

In this paper, data collection and hypothesis testing were conducted using a combination of qualitative interviews and quantitative analyses, the mixing methods that have been suggested in the prior literature to be most appropriate for the study of new constructs or performance evaluation (Zhong et al., 2021). The combination of these two approaches allowed us to drive a deeper understanding of the impact of dissonant ties on organizational innovation performance under the digital-transformation capability. Our study combines both qualitative and quantitative research approaches in terms of data. The qualitative analysis was mainly semi-structured interviews, and the quantitative analysis was a questionnaire-based empirical analysis. Combined with previous research that suggests that difficult ties tend to come from members of formal hierarchical ranks or experienced members with tenure in the organization, our first phase of questionnaire survey focused on these two categories as the issuers of problem-solving ties. The empirical setting in which we tested our hypotheses used manufacturing-industry data from Zhejiang, China SMEs.

There are several reasons for this choice. First, China is the country with the most complete industrial categories and the largest industrial scale in the world, and a series of Chinese government policies is comprehensively implementing the digital-transformation strategy of industrial industries; some enterprises have already achieved the primary results of digital transformation. Second, the small and medium manufacturing enterprises in China are selected because they have a larger space for digital transformation, clearer outcome measurement, and wider impact. Third, small and medium

Figure 1. The conceptual model



manufacturing enterprises in Zhejiang represent the biggest social network in China, with rich positive and negative ties. In addition, innovation activities are abundant in Zhejiang's manufacturing SMEs and may shed light on the relationship between dissonant ties and innovation performance. Therefore, this study selected Zhejiang's manufacturing firms as our research sample.

Specifically, for the example of constructing a dissonant-tie network, the ERGM (exponential random graph modeling) model is used in this paper for network analysis. In recent years, the ERGM model has been increasingly used to study the formation of ties in organizational networks (Lomi et al., 2014; Rank et al., 2010). This approach explains the interdependence of ties in network data (Lusher et al., 2012) and treats the occurrence of network relationships as a dependent variable. It allows us to establish a parametric logic between theoretical concerns and variables and provides a precise representation of individuals embedded in the overall network (Lomi et al., 2014). More importantly, the ERGM approach allows us to establish problem-solving and difficult ties overlapping dissonant ties separately as a function of two variable settings: network patterns linked to individual attributes (for example, describing employees embedded in organizational structures) and network endogenous structures capturing the tendency of intra-organizational network ties to transform intentional structures into self-organization (Lomi et al, 2014; Rank et al., 2010). By considering the network model two settings on the observation of problem-solving, difficult, and dissonant ties in all models, we can control for the impact of dissonant ties on innovation performance and set up an empirical study of dissonant-ties driving innovation under different stages of digital transformation.

We use the ERGM model to study the network tie characteristics and thus observe the network, based on which conclusions are drawn about organizational innovation drive. Unlike statistical methods such as regression analysis, the ERGM method explains that the observation of individual ties is not independent. It assumes that there is a stochastic process in which the presence of a particular tie is influenced by these two sets of variables: individual-attribute patterns and network-endogenous patterns. Also, the pattern of each parameter is estimated, with positive values indicating that the network pattern occurs more frequently than random ties and negative values indicating that the network pattern occurs less frequently than random ties, with conditions that apply to all other patterns in the model, establishing that the parameter values are odd probabilities taken logarithmically and can be transformed into odd ratios by exponential operations. In general, the ERGM can be expressed as:

$$\Pr\left(X = x \middle| Y = y\right) = \left(\frac{1}{k}\right)\exp\left(\sum_{Q}\theta_Q Z_Q\left(x, y\right)\right) \tag{1}$$

where X denotes a network variable with n nodes and x denotes the corresponding realization node; Y is a sequence of individual-attribute variables and y denotes the corresponding realization; $Z_Q(x, y)$ is a network statistic that calculates the number of network patterns of type Q for a particular network realization x and gives the attribute vector y; Pr is an estimate of the parameter corresponding to the statistic $Z_Q(x, y)$; and k is a normalization constant to ensure that Eq. (1) is an appropriate probability distribution. The summation result contains all network patterns (Q) included in the given model. The probability of observing any network x in this distribution (including the actual observed network x) depends on the statistic $Z_Q(x, y)$.

Based on Pattison and Wasserman (1999), the ERGM model has been extended to multiple forms and allows us to study two networks simultaneously. Based on assumptions about positive-negative network interactions in organizations, the multiple ERGM approach treats different types of ties as conditionally dependent. Therefore, $Z_Q(x)$ is a multiple conceptualization model that allows two nodes to be bound by multiple relation types:

$$Z_k\left(x\right)=\sum_{Q\in Q_k\left(i,j,m\right)\in Q}\prod x_{ijm} \tag{2}$$

where Q_k is the set of isomorphic patterns Q of the bound variables (Wang, 2013). A Markov chain Monte Carlo maximum likelihood implementation of XPNet (Wang et al., 2006) was used to estimate the parameter values for each pattern. Considering the interdependencies in the network data, all parameter estimates are similarly interdependent. That is, the interpretation of one pattern is dependent on all other patterns describing the observed network. According to the existing ERGM application (Zappa & Robins, 2016), in this paper we fix the network density to help the model converge. To reduce the effect of outliers, we further fixed the relationship with employees in each network in terms of in-degree or out-degree using standard deviation (Lusher et al., 2012).

The data collection for the empirical study was divided into two phases. The first stage was semi-structured interviews, in which we selected 10 knowledge-intensive employees from the research sample of digital transformation in manufacturing industry to conduct semi-structured interviews of about one hour each, mainly involving questions such as, "Who do you usually seek help from at work? What are your solutions to innovative and complex problems? Have you ever asked for help from someone you don't like? What are the specific tasks and challenges that the digital transformation of manufacturing presents to you? How did you deal with them?"

The main purposes of the workshop were to provide information on the digital-transformation process in practice, to further define the logic of our research topics and research themes in practice, and to conduct pre-research for the subsequent construction of social networks. We then used the roster method to establish separate positive and negative ties based on Labianca and Brass's (2006) study of network construction. Specifically, the positive network was constructed by seeking problem-solving assistance, asking, for example, "When your job requires you to engage in innovative problem-solving, who do you turn to for help in thinking outside of the box and considering the problem from a different aspect?" (Casciaro & Lobo, 2008). Negative networks were constructed through difficult relationships, asking questions such as, "Who do you think is difficult to get along with at work?" (Schulte et al., 2012). Network data were collected asymmetrically and dyad style (i.e., in the case of positive networks, the presence of positive ties was recorded as 1 and the absence of positive ties was recorded as 0).

The second stage of the empirical study was the collection of primary data and questionnaire distribution. From May to September 2021, students coming from Zhejiang manufacturing SMEs in our school's Master of Business Administration and Master of Project Management programs were invited to participate in the study. The students were asked to bring a sealed questionnaire to their top managers and were told it would not be shared with their supervisors and was only for academic usage. As a result, 389 individual observations nested in 53 work teams, located mainly in Hangzhou, Shanghai, Guangzhou, Hefei, and Nanchang, have been investigated. Overall, 274 questionnaires were retrieved. After deleting the incomplete ones, 230 usable questionnaires were obtained. Furthermore, to construct an alliance network in this study, all SMEs were from the same industry, which is the textile and clothing industry. Among those sampled firms, 30.43% are in the textile industry, 26.09% in the clothing industry, 13.04% in the printing and dyeing industry, 8.70% in the clothing ornament industry, 8.70% in the chemical industry, and 13.04% in other industries within the textile and clothing industry. The characteristics of 23 organizations and 230 questionnaires are shown in Table 1.

Measures

The basis of the variable measurement in this paper is the construction of the dissonant-tie network using the roster method and distributing the questionnaire accordingly. The three levels of dissonant-tie network structure variables contain ego multiplexity and ego at the ego level; alter multiplexity and alter at the alter level; and dissimilarity multiplexity, dissimilarity, dyadic

Table 1. Sample characteristics

Characteristics of Firms	Number of Firms	Number of Questionnaires	Percentage of Total Questionnaires
Industry Type			
Textile	7	57	24.78%
Clothing	6	49	21.30%
Printing and Dyeing	3	25	10.87%
Clothing Ornament	2	32	13.91%
Chemical	2	26	11.31%
Other	3	41	17.83%
Firm Scale (Number of Employees)			
100–500	14	156	67.83%
501–1,000	9	74	32.17%
1,001 or More	0	0	0.00%
Firm Age (Years since Establishment)			
Less than 5	8	66	28.70%
5–10	13	119	51.74%
11 or More	2	45	19.56%

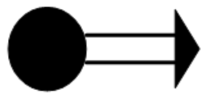
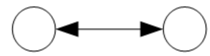
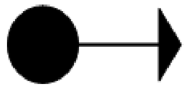
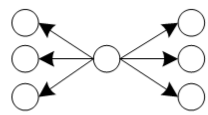
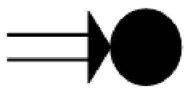
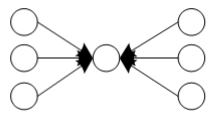
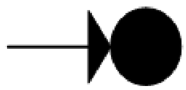
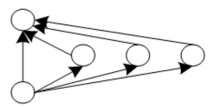
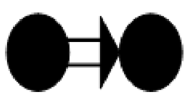
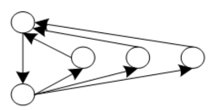
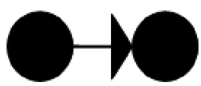
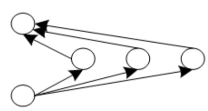
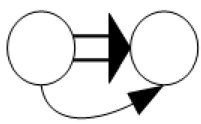
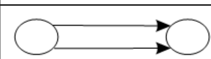
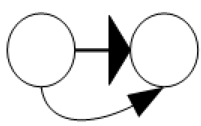
entrainment multiplexity, and dyadic entrainment at the dyad level. The three-level variables correspond to different property measures of network endogeneity as reciprocity, activity spread, popularity spread, transitive closure, cyclic closure, multiple connectivity, and general connectivity. The structure and content measures at the alter, dyad, and ego levels of the dissonant-tie network are shown in Table 2.

Regarding the measure of the independent variable dissonant tie, this paper refers mainly to the research results of Battilani et al. (2018), Brennecke (2020), and Hornstra et al. (2022) and understands dissonant ties in terms of positive ties and negative ties, with positive ties consisting of problem-solving ties and negative ties consisting of ties that are difficult to get along with at work. This paper relies mainly on the Ghosh et al. (2022), Gökalp & Martinez (2021), and Matarazzo et al. (2021) studies to set the moderation variables. The studies all used a 1–5 Likert scale to measure the variables. The specific variable measurement scales are shown in Table 3.

Reliability and Validity

As previously mentioned, those items and the models in this study were based on the existing literature, having already been validated by other researchers. To further examine the variables' reliability, Cronbach's α was applied to test through SPSS software. As shown in Table 4, all scales were reliable, with values ranging from 0.623 to 0.745, demonstrating good construct validity in this research. Furthermore, KMO and Bartlett's tests were used to detect the related items of innovation performance, dissonant ties, and digital-transformation capability. The results indicated each variables' items can be combined into one factor by exploratory factor analysis and confirmatory factor analysis for subsequent intervariable relationship analysis. In addition, the value of RMSEA < 0.05 and GFI, CFI, and IFI all being more than 0.9 also indicated the validity of variables in our study.

Table 2. Ego, dyad, and alter levels of dissonant ties

Variable	Visualization	Network Statistics	Variable	Visualization	Network statistics
Ego Multiplexity		$\sum x_{ijm}y_i$	*Reciprocity*		$\sum x_{ij}x_{ji}$
Ego		$\sum x_{ij}y_i$	*Activity Spread*		$\sum_{k=2}^{n-1}\left(-1\right)\frac{kS_{k\_out}}{»^{k-2}}$
Alter Multiplexity		$\sum x_{ijm}y_j$	*Popularity Spread*		$\sum_{k=2}^{n-1}\left(-1\right)\frac{kS_{k\_in}}{»^{k-2}}$
Alter		$\sum x_{ij}y_j$	*Transitive Closure*		$»\sum_{i<j} x_{ij}\left\{1-\left(1-\frac{1}{»}\right)^{L_{C2ij}}\right\}$
Dissimilarity Multiplexity		$\sum x_{ijm}y_iy_j$	*Cyclic Closure*		$»\sum i < jx_{ij}\left\{1-\left(1-\frac{1}{»}\right)^{L_{T2ij}}\right\}$
Dissimilarity		$\sum x_{ij}y_iy_j$	Multiple Connectivity		$»\sum_{i<j}\left\{1-\left(1-\frac{1}{»}\right)^{L_{T2ij}}\right\}$
Dyadic Entrainment Multiplexity		$\sum x_{ijm}v_{ij}$	General Connectivity		$\sum x_{ijm}$
Dyadic Entrainment		$\sum x_{ij}v_{ij}$			

RESULTS

Descriptive Statistics and Correlations

Table 5 shows the mean, standard deviation, and correlation coefficients of problem-solving ties, difficult-working ties, digital sensing and seizing, digital reconfiguring, each control variable, and innovation performance (IP) analyzed and measured using SPSS, and it can be seen that the correlations among the variables have been initially revealed through the basic descriptive statistics. The results of descriptive statistics show that the correlation coefficients among independent variables are less than 0.7, indicating that the correlations among variables are not significant. The maximum correlation coefficient with IP was (0.531, $p < 0.05$). Also, the variance inflation factor (VIF) was calculated in this paper, and the results showed that the VIF for each direct variable ranged from 2.942 to 5.000. This is below the critical value of 10 for measuring the VIF. The tolerance took values from 0.235 to

Table 3. Details of items measured by each index

<table>
<tr><th>Variable</th><th>Dimension</th><th colspan="2">Item</th></tr>
<tr><td rowspan="8">Dissonant Tie</td><td rowspan="3">Problem-Solving Tie</td><td>PT1</td><td>When there is a problem, I tend to seek a solution from someone in a higher position</td></tr>
<tr><td>PT2</td><td>I tend to seek problem-solving from people with higher titles when I encounter problems</td></tr>
<tr><td>PT3</td><td>When faced with a problem, I tend to look to higher performers for problem-solving</td></tr>
<tr><td rowspan="5">Difficult-Working Tie</td><td>DT1</td><td>I care more about problem-solving than emotional pleasure in my work</td></tr>
<tr><td>DT2</td><td>I seek heterogeneous knowledge in my work and want more access to unique resources</td></tr>
<tr><td>DT3</td><td>My views are often challenged and questioned when seeking solutions to problems</td></tr>
<tr><td>DT4</td><td>I feel insecure and burdened when seeking solutions to my problems</td></tr>
<tr><td>DT5</td><td>I am always stressed when seeking solutions to problems</td></tr>
<tr><td rowspan="9">Digital Transformation Capability</td><td rowspan="5">Digital Sensing and Digital Seizing</td><td>DSS1</td><td>We are sensing external and internal environments continuously for new digital initiatives</td></tr>
<tr><td>DSS2</td><td>We are scouting external environments with our partners for new digital business opportunities</td></tr>
<tr><td>DSS3</td><td>We develop product prototypes rapidly</td></tr>
<tr><td>DSS4</td><td>We have implemented lean product development methodology</td></tr>
<tr><td>DSS5</td><td>We created specific business groups for industrial internet of things and digital transformation</td></tr>
<tr><td rowspan="4">Digital Reconfiguring</td><td>DR1</td><td>We are developing capabilities to move from a product-centric business model to a service-centric business model</td></tr>
<tr><td>DR2</td><td>We are experimenting with a pay-per-use business model</td></tr>
<tr><td>DR3</td><td>Our managers believed having data to drive decision-making capability for digital transformation</td></tr>
<tr><td>DR4</td><td>Our managers have a digital mindset for digital transformation</td></tr>
<tr><td colspan="2" rowspan="5">Innovation Performance</td><td>IP1</td><td>We have increased the number of patent applications</td></tr>
<tr><td>IP2</td><td>Our innovative product coverage has expanded</td></tr>
<tr><td>IP3</td><td>We have increased the success rate of our innovative products</td></tr>
<tr><td>IP3</td><td>We have increased our input costs for our innovative products</td></tr>
<tr><td>IP4</td><td>Our rate of innovative product development has increased</td></tr>
</table>

Table 4. Reliability and validity of variables

Variables	Cronbach's α	λ/*df*	RMSEA	GFI	CFI	IFI
PT	0.652	1.823	0.044	0.945	0.920	0.931
DT	0.633	1.925	0.027	0.933	0.939	0.922
DSS	0.745	1.854	0.028	0.967	0.908	0.924
DR	0.664	1.888	0.033	0.982	0.902	0.959
IP	0.625	1.807	0.038	0.909	0.935	0.936
NSH	0.725	1.923	0.039	0.933	0.922	0.917
NDC	0.627	1.817	0.036	0.927	0.900	0.929
LE	0.623	1.959	0.043	0.956	0.939	0.922
WA	0.654	1.514	0.041	0.910	0.924	0.944
ST	0.658	1.624	0.039	0.991	0.951	0.906

Note: PT, problem-solving tie; DT, difficult-working tie; DSS, digital sensing and seizing; DR, digital reconfiguring; IP, innovation performance; NSH, network structure hole; NDC, network degree centrality; LE, level of education; WA, work age; ST, team similarity.

0.433, which is greater than the recommended lower limit of 0.100 (Table 6). The results also show that the relevant data involved in the variables of this paper do not have the problem of multi-collinearity.

Table 5. The means, standard deviations, and Pearson coefficients of variables

Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10
1. PT	2.325	0.649	1									
2. DT	2.549	0.602	0.220	1								
3. DSS	3.202	0.574	0.153	0.184	1							
4. DR	3.032	0.439	0.409	0.322	0.239	1						
5. NSH	3.270	0.400	0.393	0.343	0.230	0.214	1					
6. NDC	3.483	0.366	0.208	0.208	0.163	0.207	0.267	1				
7. LE	6.219	4.606	-0.225*	-0.152*	-0.258	0.343	-0.302**	0.250*	1			
8. WA	1.233	0.637	0.109*	0.258*	0.220	0.231**	0.233**	0.242	0.331	1		
9. ST	4.023	0.643	0.531*	0.272*	0.308	0.144	0.459**	0.219	-0.153	0.121*	1	
10. IP	3.553	0.685	0.222*	0.144*	0.145*	0.393	0.360	0.340**	0.344**	0.291	0.236	1

Note: $P < 0.05$; $^{**}P < 0.01$; $^{***}P < 0.00$

Hypotheses Testing

To further verify the hypotheses of this paper, the regression analysis was conducted using multilevel linear regression method and SPSS software. Five submodels were developed for the regression analysis, and the F-values of the holistic statistical tests for each model reached significance ($p < 0.001$), indicating that the overall explained variance of each model reached a significant level. Table 6 shows the results of the analysis of the stratified regression, the design standardized coefficient estimates, R^2, adjusted R^2, and F-values. The specific steps of the regression follow.

Table 6 shows the results of the regression analysis. Specifically, Model 1 shows the correlation coefficient of control variables on the dependent variable innovation performance (IP), and the results show that there is a negative effect of dissonant-tie network structure hole (NSH) on organizational innovation performance; that is, the more dissonant-tie network structure holes, the lower the organizational innovation performance. There is a positive relationship of dissonant-tie network centrality (NDC) on organizational innovation performance; that is, the higher the dissonant-tie network centrality, the higher the organizational innovation performance. There is a positive relationship between members' level of education (LE) and work age (WA) on innovation performance, which proves that members are more inclined to seek problem-solving help from members with higher ranks or longer work experience, and these members may also have more difficult professional attributes. Team dissimilarity can help members with out-of-box thinking, and thus there is a negative effect of team similarity (ST) on innovation performance.

In Model 2, the independent variables problem-solving tie (PT) and difficult-working tie (DT) were added to our model, and the results showed a positive correlation with the dependent variable IP ($\beta = 0.239$, $p < 0.01$; $\beta = 0.256$, $p < 0.01$); thus, Hypothesis 1 was supported. This is in line with this paper's theoretical development. Mueller and Kamdar (2011) argue that positive ties such as problem-solving ties and negative ties such as difficult-working ties exist simultaneously in networks and contribute to organizational performance. This study also conducts an in-depth analysis of the impact of dissonant ties on organizational innovation in the context of the belief that dissonant ties, consisting of both problem-solving and difficult-working ties, facilitate the acquisition and transmission of heterogeneous knowledge among members, the fermentation and absorption of innovations, and the questioning of established ideas, thus enhancing organizational exploratory innovation.

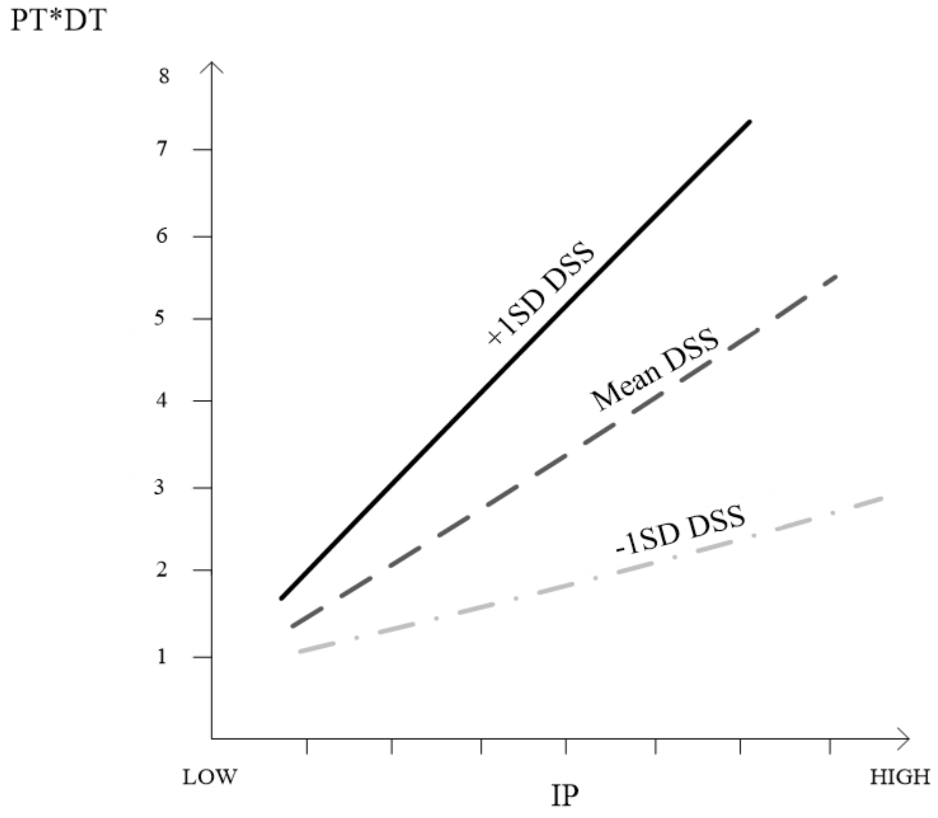
In Models 4 and 5, first, the positive effect of PT and DT on IP was facilitated by the moderating effect of DSS ($\beta = 0.202$, $p < 0.001$). This indicates that the dissonant tie of organizational innovation is reinforced by more digital sensing and seizing inside and outside the organization (figure 2). Hypothesis

Table 6. The results of regression analysis

	Model 1	Model 2	Model 3	Model 4	Model 5	Multi-Collinearity	
			IP			Tolerance	VIF
IV							
PT		0.239** (2.202)		0.214** (1.557)	0.288*** (2.519)	0.239	3.234
DT		0.256** (3.275)		0.188** (2.514)	0.267*** (3.218)	0.332	3.303
PT × DT		0.204** (3.058)		0.229** (3.517)	0.225** (1.324)	0.395	3.852
DSS			0.232* (3.201)			0.254	2.942
DR			-0.205 (2.374)		0.377 (3.254)	0.334	5.000
PT × DT × DSS				0.227*** (1.080)		0.352	4.302
PT × DT × DR					0.158 (2.501)	0.333	4.583
CV							
NSH	-0.132 (3.032)	-0.221** (3.230)	-0.224** (4.302)	-0.293 (4.236)	0.149 (3.432)	0.235	4.030
NDC	0.328** (3.112)	0.222 (2.904)	0.220** (3.242)	0.112 (3.838)	0.209 (2.005)	0.304	4.340
LE	0.200** (3.431)	0.331** (2.042)	0.367** (3.200)	0.204 (2.483)	0.286** (4.237)	0.433	3.031
WA	0.139** (3.932)	0.204 (3.283)	0.129** (2.603)	0.353 (3.119)	0.231 (2.545)	0.366	4.733
ST	-0.204* (2.303)	-0.344 (3.583)	-0.332 (2.572)	-0.232 (2.453)	-0.249** (3.200)	0.414	4.832
R^2	0.215	0.248	0.278	0.322	0.315		
Adjusted R^2	0.211	0.246	0.276	0.320	0.313		
F	10.585	8.252***	8.392***	10.263***	11.029***		

2 was supported. Second, the effect of PT and DT on IP was not significant under the moderating effect of DR ($\beta = 0.291$, $p > 0.05$). That is, in the context of digital reconfiguring, dissonant ties are not an effective way to promote organizational innovation performance, and Hypothesis 3 was not supported. On the one hand, during digital reconfiguring, the knowledge and relationship structure holes in the organization are reorganized, new individual hires occur so that previously lost ties are replaced, and new ways of working and organizational routines are gradually formed as organizational members learn and adapt to each other in new ways. On the other hand, during digital reconfiguring, the possible knowledge resources, the challenge to opinion seekers' viewpoints, and the cognitive catalyst function provided by difficult working ties are weakened in the process of forming new organizational practices and stability.

Figure 2. Moderating effects of digital sensing and digital seizing on the relationship between dissonant ties and innovation performance



Robustness Testing

This paper tests the robustness of the results of multiple regression analysis by two methods. First, the study of the effect of dissonant ties of the independent variable on the innovation performance of the dependent variable at different stages of digital-transformation capability has a certain process orientation, as existing studies have made it clear that seeking heterogeneous knowledge help can increase organizational innovation. In this paper, the results are verified by replacing organizational innovation performance with the dependent variable organizational adaptability and the incremental organizational performance brought by the increase in market share of the same type of product as the dependent variable measure.

Second, although the control variables in this paper involved mostly individual characteristics and attributes when conducting multiple regressions, formal hierarchical rank or tenure were also shown to also influence the effect of dissonant ties on organizational innovation performance under different stages of digital-transformation capability. Therefore, we included these two control variables in the robustness test, adding them for the re-step test. The results showed no difference from the original main regression test. In summary, after two methods of robustness testing, the final regression analysis results showed no significant change from the main test, indicating that the results of this paper's empirical study are robust.

CONCLUSION AND DISCUSSION

The purpose of this paper is to decipher how dissonant ties, which are composed of problem-solving ties and difficult-working ties among members, affect organizational innovation performance in the digital-transformation capability scenario. The empirical analysis of this paper leads to the following main conclusions.

First, the construction of dissonant ties is conducive to the generation of organizational innovation performance. The dissonant tie can provide innovative solutions to complex problems in teams through the unique relational resources and knowledge heterogeneity it provides. More importantly, the tension between the problem-solving tie and the difficult-working tie can accelerate the efficiency of the problem-solving tie to a certain extent and thus increase the speed of innovation. Based on social-ledger theory, social-network theory, and cognitive-dissonance theory, this paper verifies that positive and negative ties may exist between the same pair of individuals and enriches the previously held impression that positive ties bring positive effects while negative ties bring negative effects in social networks.

Second, dissonant ties do not always contribute to organizational performance. Dissonant ties at the three levels of alter, dyad, and ego do not have the same impact on organizational performance. Going beyond one's network path dependency to seek problem-solving help from difficult organizational members requires additional emotional and time costs. Dissonant ties do not always contribute to the improvement of organizational innovation performance, and moderate dissonant ties can help organizations survive digital transformation.

Third, the different components of digital-transformation capability have different impacts on organizational innovation. This paper argues that digital-transformation capability consists of digital sensing, digital seizing, and digital reconfiguring. Digital sensing and digital seizing have a positive influence on the relationship of dissonant ties and innovation performance; however, digital reconfiguring's moderating positive influence on the relationship of dissonant ties and innovation performance has not been verified. Theoretically, the research in this paper helps us to recognize the stage-specific and dynamic nature of the moderating effect of DTCs on the relationship between dysfunctional connections and organizational innovation. In the different stages of data extraction and digital reconstruction, the dysfunctional connections consisting of problem-solving links and difficult-to-get-along-with links can promote organizational innovation, while in the stage of digital reconstruction, the dysfunctional connections among individuals do not bring new increments of innovation but may consume unnecessary resources and costs. In the digital-reconfiguring phase, companies need to establish mechanisms to encourage more heterogeneous communication and provide a platform for employees to seek advice from them. While in the digital-reconfiguring phase, companies need to maintain the balance between innovation and resource cost by strengthening links between employees and reducing cross-departmental and cross-type collaboration.

Regarding the research outlook of this paper, on the one hand, the digital-transformation capability issue as a core issue of dynamic-capability theory and innovation scope based on the need to study in the face of digital change, the organizational practices under its influence, multiple organizational networks and organizational noncontractual governance-related issues still need to be studied in depth. On the other hand, as a way of multiple ties between individuals, dissonant ties as a possible negative impact of organizational innovation will also be the next research direction of the team.

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