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Speeding up decision-making in project environment: The effects of decision makers' collaboration network dynamics

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Abstract

Faced with continuously changing project environments, organizations need to not only make the right decisions but also make decisions in a timely manner. This study investigates the determinants of timely decision-making from the perspective of collaboration network dynamics. From the archival data recordings of the decision-making meetings of Program N, a national water transfer program, the meeting-based collaboration relationships of the decision makers were identified. Cox regression was employed to explore the effects of collaboration network dynamics on the time needed to reach a decision. The results suggest that stronger previous collaboration relationships and more centralized social capital distribution in decisions groups contribute to more timely decision-making. These findings substantiate social network theories in a real-world collaborative decision-making setting and reveal the facilitators of timely project decisions. The practical implication for project decision management is that the recruitment of a decision-making group should be based on not only the decision makers' technical expertise but also their collaboration network dynamics.

Keywords: Project decision-making; Collaboration network dynamics; Project decision speed

1. Introduction

Project management techniques, partly originating from operations research and decision science, are inherently decision-oriented (Kwak and Anbari, 2009; Söderlund, 2011) as evidenced by some widely adopted methods, e.g. CPM (Critical Path Method) and AHP (Analytic Hierarchy Process) (Bakht and El-Diraby, 2015). In essence, decision management is an integral part of project management (Hazır, 2015; Stingl and Geraldi, 2017), and decision problems exist in almost all management hierarchies of project-based organizations (Beringer et al., 2013). As more and more firms organize their business by projects, the effectiveness and timeliness of project decisions have an increasingly profound influence on the strategic development of organizations (Eweje et al., 2012; Wen and Qiang, 2016b). Despite the aforementioned project management tools, techniques and their increasingly sophisticated extensions, many organizations still suffer from problems in decision-making (Dayan et al., 2012; Luoma, 2016), such as escalation of commitment (Lechler and Thomas, 2015), optimism bias (Beringer et al., 2013), gold plating (Stingl and Geraldi, 2017) and decision delays (Assaf and Al-Hejji, 2006). These problems point to the behavioral dimension of decision-making and indicate that employing advanced tools or techniques is not a silver bullet for real-world decision problems (Luoma, 2016; Stingl and Geraldi, 2017).

In ever-changing project environments, decision-making becomes an information-intensive process with a critical influence on the time-to-market of projects (Dayan et al., 2012). The intensive dependencies among various project tasks make it difficult for a single decision maker to tackle complex project decision problems based on the limited information s/he owns. Many organizations (especially public organizations) heavily rely on collaborative decision-making groups, in which experts form close collaboration

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relationships and contribute their insights to reach a rational decision (Bakht and El-Diraby, 2015; Jaber et al., 2015). Group decision-making benefits from multidisciplinary information but also brings challenges to the timeliness of decisions, which is particularly crucial for adapting to the changes in project environments (Eweje et al., 2012; Sun et al., 2008). First, the coordination and communication among multiple decision makers may consume considerable time and delay the decision (Dayan et al., 2012). Second, sharing knowledge and reaching consensus within decision-making groups calls for trust and mutually agreed on objectives, which however are not easily established in a short time span as group size expands (Buvik and Rolfsen, 2015). Third, the one-off nature of project decisions leads to the lack of formally defined implementation routine and may further cause the decision process to be loosely organized (Bergman et al., 2012; Sun et al., 2008).

Taken together, decision speed stands out as a major challenge in group-based project decision-making, significantly influenced by the relational and behavioral aspects of decision groups (Dayan et al., 2012; Eweje et al., 2012). Decision groups should be developed into collaborative networks of contributors rather than collections of competitors pursuing incongruent interests (Jaber et al., 2015; Stingl and Geraldi, 2017). However, how collaboration network dynamics affect project decision making remains largely unexplored, and hence, there is a lack of understanding on how to enable timely decisions by creating effective decision groups (Luoma, 2016). Heeding the call for analyzing the group dynamics among decision makers (Bakht and El-Diraby, 2015; Giannoccaro and Nair, 2016), this study explores the facilitators of timely project decisions from a dynamic collaboration network perspective.

Research question: How do the dynamics in the collaboration network of decision makers influence the timeliness of project decision?

The rest of the paper is organized as follows. The second section reviews the literature on project decision-making and collaborative decision-making groups and, based on this, develops the research hypotheses. The third section elaborates on the empirical analysis procedure, including data collection, dynamic social network analysis and the Cox regression model for hypothesis testing. The analysis results are presented in the fourth section and further discussed in the fifth section with respect to their implications for project decision management research and practice. The sixth section concludes the paper, discusses its limitations and proposes future research directions.

2. Literature review

2.1. Project decision: pursuing timeliness in temporary collaboration

Project decision-making has long been a hot topic in project management research and practice (Bakht and El-Diraby, 2015). The majority of research efforts have been devoted to developing decision support models (Hazır, 2015), and it is not until the last ten years that the behavioral dimension of decision-making has been studied (Stingl and Geraldi, 2017).

Following the progress in operations research and decision science, one stream of project management research applied decision models and techniques to project decision management (Bakht and El-Diraby, 2015). For example, CPM (Critical Path Method) started to prevail in 1960s. The fuzzy logic method has become widely adopted since 1970s–1980s. Expert systems and simulation methods represented the major developments of decision techniques in 1990s. The beginning of the 20th century witnessed the prevalence of AHP (Analytic Hierarchy Process) and various heuristic algorithms. Being applied to decision-making in nearly all project management processes from initiation to closing, these methods serve as valuable tools for project decision management (Hazır, 2015; Liberatore and Pollack-Johnson, 2013). However, as the models involve more and more sophisticated methods, they risk being less and less easily applied in practice (Luoma, 2016). Most of the models implicitly assumed that decision-making is straightforward with sufficient information on model parameters, but overlooked the decision process, which, if delayed, may undermine the validity of the decision, especially in dynamic project environments. Based on a systematic review on decision support models, Luoma (2016) pointed out that decision models cannot perfectly solve decision problems without considering organization contexts. They work better for well-defined optimization decisions but are less flexible for problem-solving oriented decisions. However, the majority of real-world project decisions are unique and problem-solving oriented. As the complexity of decision models grows, the time and efforts needed for model applications also grow undermining their applicability in practice (Bakht and El-Diraby, 2015). This partly explains why some quick-and-dirty methods (such as Earned Value Analysis, EVA) are still widely utilized in practice (Hazır, 2015; Luoma, 2016).

On the other hand, there has been growing research on the behavioral effects of decision makers. Beringer et al. (2013) identified project selection, resource allocation and project monitoring as the three major processes in portfolio management. According to Beringer et al. (2013), advanced decision models do not ensure rational decisions, and coordinating four types of internal stakeholders (i.e. top management, functional manager, portfolio manager and project manager) is crucial for decision quality and speed. Eweje et al. (2012) further argued that coordinating both internal and external stakeholders is especially important for decisions-making in mega projects, characterized by long duration and hyper-sensitivity to risks. Based on a literature review of behavioral decision-making in projects, Stingl and Geraldi (2017) identified the lack of research on decision speed compared with the abundant research on decision quality. The uniqueness of projects leads to the lack of a reference point to determine what if an alternative decision were made, and the evaluation of decision quality is also criticized for hindsight bias (or retrospective bias) (Riccobono et al., 2016; Winch and Maytorena, 2009). In rapidly changing project environments, making a timely decision with acceptable quality is more practical than spending too much time and cost on optimizing decisions and risk missing opportunities in market (Dayan et al., 2012; Luoma, 2016).

According to the two streams of studies reviewed above, more and more research attention has been shifted from the optimization

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to the timeliness of decisions (Eweje et al., 2012), from decision model development to the behavioral aspects (Stingl and Geraldi, 2017), and from individual to collaborative decision-making (Bakht and El-Diraby, 2015). Following this trend and considering the dynamic project environments, this study specifically focuses on the challenge of accelerating decision speed in temporary collaborative decision groups.

Although group decision-making is increasingly applied, there is still a paucity of research on the enablers of efficient group decision-making (Giannoccaro and Nair, 2016). On the other hand, the behavioral dynamics of project decision groups remain largely unexplored. In fact, project decision groups have long been studied as teams undertaking one-off/single-session decisions in organization behavior (OB) research (Harrison et al., 2003). Several insightful theories, such as Time-Interaction-Performance (TIP), Groups as Complex Systems (GCS) and Social Entrainment Theory (SET), have been proposed to explain temporary team effectiveness. However, these studies are not specific to the dynamic project environment, where decision speed becomes a major concern (Stingl and Geraldi, 2017). Informed by this research gap, this study aims to establish the dialogue between project management and mainstream OB research by analyzing how the collaboration dynamics of decision groups influence decision speed.

2.2. Collaborative decision making: a dynamic network perspective

Despite the fleeting nature of project decisions, each decision is not independent from the context of the permanent organization, within which decision makers maintain long-term collaboration relationships (Beringer et al., 2013; Lechler and Thomas, 2015). The simulation study of Taylor et al. (2009) reveals that the dynamic network formed via collaborations significantly influences team learning and team effectiveness (although the study is conducted at firm-level, the findings are easily extensible to team-level). Jaber et al. (2015) further pointed out that social network analysis (SNA) should be employed to derive managerial insights from the network established in collaborative decision-making activities. In this light, we build our study of collaborative project decision-making on a social network theory perspective.

One stream of social network theory focuses on the strength of network ties, represented by the well-known weak tie theory by Granovetter (1973). The weak tie theory emphasizes the strength of weak ties in bringing access to novel information and resources. However, Granovetter (1973) specifically pointed out that the weak tie theory by no means denies the value of strong ties, instead, it suggests considering different tie strengths for different analytical purposes. In project environments characterized by frequent staff turnover and changes in collaboration relationships, strong ties established via repeated collaborations are reported to be beneficial in many previous studies (Buvik and Rolfsen, 2015; Reagans et al., 2004; Savelsbergh et al., 2015). Especially in Jaber et al.'s (2015) study on decision group member selection, intensive previous collaborations (strong ties) are implicitly assumed to improve collaborative decision-making. The positive effects of strong ties on group decision-making have also been echoed in many organization behavior (OB) studies (Harrison et al., 2003; Kurvers et al., 2015). In experiment settings, the collaboration experience and familiarity among group members were found to be associated with superior communication efficiency, decision quality and decision speed (Harrison et al., 2003; Kurvers et al., 2015; Riccobono et al., 2016). However, in a real-world project setting, there is a lack of empirical evidence on how collaboration tie strength affects the timeliness of decision. There also exist some arguments pointing to the negative effects of strong ties (Brockman et al., 2010). For example, common blind spots are more likely to exist in a group of strongly connected decision makers and may hinder timely solutions to the decision problems (Hällgren, 2010; Stingl and Geraldi, 2017). Thus, this study aims to empirically examine the following hypothesis in real-world project decision-making:

Hypothesis 1. The familiarity (number of collaboration experiences) among decision group members positively affects project decision speed.

Another stream of social network theory focuses on the strength of network positions, represented by social capital theory (Coleman, 1988). An individual's social network position, measured in centrality, directly relates to power and influence in the network and can be regarded as an implicit capital. Individuals with higher centrality assume central roles in communication and tend to perform relational leadership in collaboration network (Borgatti et al., 1998; Mizruchi and Potts, 1998). Previous empirical evidence suggests that the distribution of social capital in project teams significantly affects knowledge sharing (Bartsch et al., 2013; Batallas and Yassine, 2006; Wen and Qiang, 2016a), collaboration (Han and Hovav, 2013; Wen et al., 2017) and overall project performance (Di Vincenzo and Mascia, 2012). On the one hand, centralized social capital distribution indicates the existence of coordinators that hold central network positions and bridge the conversation between the members who have less previous collaboration experience (Hollingshead, 2001; Mizruchi and Potts, 1998; Mukherjee, 2016). In this way, such relational leaders enable better coordinated collaboration, and hence improves group decision efficiency (Bergman et al., 2012). On the other hand, some studies argued that social capital centralization may cause a few members to dominate decision processes, hinder multidisciplinary knowledge integration and impede timely solutions to decision problems (Hällgren, 2010; Riccobono et al., 2016). Thus, the effects of team social capital distribution on project decision-making is controversial, and the competing arguments remain to be empirically tested. Several studies implied general supports to the positive effects of social capital centralization (Bunderson, 2003; Gloor, 2016; Mukherjee, 2016). However, there is a lack of empirical evidence specific to project decision-making groups and the timeliness of project decision, and this study aims to bridge this gap.

Hypothesis 2. Group social capital centralization (high concentration in social capital distribution) in decision-making groups positively affects project decision speed.

From the theoretical lens of social network theory, the above two hypotheses operationalize the research question into the conceptual model to be tested in this study. Most existing studies on project decisions adopted cross-sectional research design, which cannot fully reflect the dynamics in collaborative decision-making and tend to suffer from hindsight bias (Hällgren, 2010; Winch and Maytorena, 2009). In fact, both group collaboration experience and social capital distribution build on members' collaboration history and are inherently dynamic. As pointed out by McGrath et al. (1993), using cross-sectional data to study dynamic organization behaviors risks introducing two types of biases, i.e. short-term effects disappearing in long-term and long-term effects not fully captured in short-term. In this light, this study performs dynamic SNA to analyze the evolution of the collaboration relationships among decision makers and test the hypotheses with longitudinal data.

3. Research methods

3.1. Data collection

Project decisions in the Chinese national water transfer program N were selected as a sample ideally suited for the purpose of this study due to the following advantages:

1. Program N is the world's largest water transfer program with many record-breaking attributes (e.g. the channel length, the population benefitting from the program and water transfer capacity). The program includes >1400 km water channels in total. Nearly all types of hydraulic engineering structures (dams, hydropower stations, aqueducts and tunnels, etc.) are integrated, so it is widely appreciated as a live encyclopedia of hydraulic engineering. In fact, it includes the majority of recent water transfer projects in China. Thus, the projects in program N are representative of China's water transfer industry in terms of technical, project management and decision-making practices.
2. The program started in 2002, the construction work was completed in 2013, and various auxiliary projects are still under construction. Due to the complexity and the significant influence of the program, an expert committee was established in 2004 to support important decisions in the program. The committee consists of 67 distinguished experts in hydraulic engineering. It involves nearly all Chinese Academy of Science and Chinese Academy of Engineering members in related fields (including civil engineering, transportation, hydrology, ecology) to integrate top expertise in multiple disciplines. Each time a project in Program N faces a tough decision problem, the experts with relevant expertise will be invited to a decision meeting, during which they voluntarily share professional knowledge to reach a rational decision on that problem. The collaborative decision meetings enable the development of collaboration relationships and provide a rich data source for this study.
3. Since its foundation in 2004, the expert committee has hosted 157 decision-making meetings corresponding to the decision problems (some decision problems may be discussed more than once). Through the 157 decision groups, the 67 committee members have formed a continuously growing collaboration network. The full records of the 157 meetings enable the analysis on how the network grew from the very beginning to its current state and how the network dynamics in this process affect decision-making. This longitudinal research design avoids the hindsight bias and makes the results eligible for causal inference.

In order to obtain comprehensive data of the decision groups, the researchers interviewed the committee's executive assistants to understand the organization form of the committee, obtain the basic information of the experts and retrieve the document records. After that, we held a workshop with the vice chair and secretary of the committee to discuss the advantages and disadvantages of group decision-making, and the factors influencing the timeliness of project decisions. We also made field trips to the five major project sites to investigate the actual execution and the influence of the project decisions. The reports from the official website of Program N were collected as supplementary data for triangulation.[1] Taken together, we obtained the list of the committee members, the document records (describing the date, major participants and theme of each decision meeting) and the photo records of the meetings. Based on these data, we designed an empirical analysis procedure (Fig. 1) to derive the meeting-based collaboration network and conduct further analysis.

3.2. Data preprocessing

To identify the participants of each meeting, we separately coded the photo and document data based on the list of committee members and their photos publicly available on the committee's official website. In this way, we constructed a dataset including the 969 participants of the 157 meetings (a committee member may attend more than one meeting). Comparing the results with the five meeting check-in lists gathered from project sites,[2] we found that all the expert committee members' participation in the five meetings were reflected in the dataset. Some participants from the local project teams were not reflected. This is because the local project team participants were invited to provide supporting information and hence not recorded as the main decision makers in text or photo records. Based on this fact, we consider the dataset to capture the collaboration among the committee members as the major decision makers and used it to analysis the series of 157 collaborative decisions. Following previous studies (Batallas and Yassine, 2006; Jaber et al., 2015), we organized the data with a matrix **MP** (bi-partite network), in which each row represents a meeting, each column represents a committee member, and the element $\mathbf{MP}_{ij}$ in row i and column j equals 1 if member j attended meeting i or 0 otherwise.

For the m_{th} decision meeting, the previous collaboration relationships can be derived for each pair of committee members in earlier meetings based on the first m-1 rows of **MP**. Specifically,

[1] http://www.nsbd.gov.cn/zx/nsbdjswyh/, retrieved on March 2nd, 2017.

[2] Some projects used check-in lists to record the participants who actually attended, and we were able to collect 5 lists.

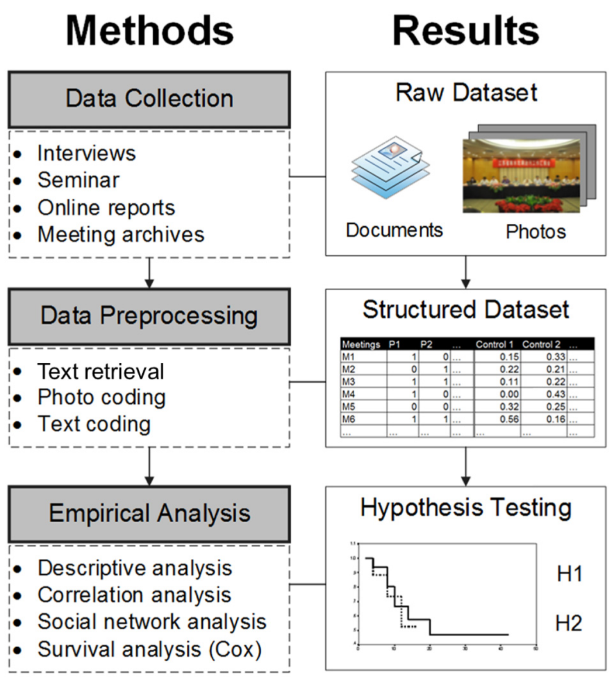

Fig. 1. Empirical analysis procedure. Note: the variable values and curves in the figure are only illustrative examples.

we calculated the adjacency matrix $\mathbf{PP}_{m-1}$ (unimodal network) of the collaboration network (Jaber et al., 2015):

$$\mathbf{PP}_{m-1} = (\mathbf{MP}_{m-1})^T \mathbf{MP}_{m-1} - \operatorname{diag}\left[(\mathbf{MP}_{m-1})^T \mathbf{MP}_{m-1}\right]$$

where each element $\mathbf{PP}_{m-1kl}$ are the number of collaboration experiences between members k and l until the m_{th} meeting (the diagonal elements were subtracted to eliminate members' collaborations with themselves). Based on the existing collaboration network before each meeting, we calculated the dependent, independent and control variables in the conceptual model, as listed in Table 1 and explained in the following sections.

3.2.1. D1. Decision time

For each decision meeting, the time taken for the expert group to reach a final decision was coded from the text documents (in unit of days) to directly measure decision speed.

3.2.2. I1. Group familiarity

The dataset fully records the meeting-based collaborations since its inception, so the average collaboration experiences among the m_{th} decision meeting participants can be calculated to reflect the familiarity level of the m_{th} decision group within this organization context. Based on the collaboration network $\mathbf{PP}_{m-1}$ before the m_{th} decision meeting, the group familiarity is calculated as

$$\textit{Group familiarity}_m = \frac{(p_m)^T * \mathbf{PP}_{m-1} * p_m}{\left[(p_m)^T * p_m\right] * \left[(p_m)^T * p_m - 1\right]}$$

where p_m is a N dimensional (the number of committee members) binary vector indicating whether each member participated in the m_{th} decision meeting (1 for those who participated, 0 otherwise); the numerator is the amount of existing collaborations between the m_{th} meeting participants

Table 1
Variables in the model.

Category	Variable	Calculation method	Reference
Dependent variable	Decision time (D1)	Meeting document coding	Specific to this study
Independent variables	Group familiarity (I1)	SNA (PP matrix)	Riccobono et al. (2016)
	Social capital centralization (I2)	SNA (PP matrix)	Mukherjee (2016)
Control variables	Number of participants (C1)	SNA (PP matrix)	Reagans et al. (2004)
	Discipline diversity (C2)	Information on experts	Reagans et al. (2004)
	Authority centralization (C3)	Information on experts	Riccobono et al. (2016)
	Decision problem level (C4)	Meeting document coding	Specific to this study
	Decision problem type (C5)	Meeting document coding	Specific to this study

Note: The calculations are based on the raw information in the meeting records.

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before the m_{th} meeting; the denominator is the number of all possible collaborations between the m_{th} meeting participants. *Group familiarity$_m$* is the average number of pre-existing collaboration experiences in the m_{th} decision group. Besides, longer previous meeting durations may lead to more abundant collaboration experience and higher familiarity level. So we calculated an alternative measure of *Group familiarity′$_m$* using the duration of the previous $m-1$ meetings as weighting factors.

$$Group\ familiarity'_m = \frac{(p_m)^T * \mathbf{PP'}_{m-1} * p_m}{\left[(p_m)^T * p_m\right] * \left[(p_m)^T * p_m - 1\right]}$$

where,

$$\mathbf{PP'}_{\boldsymbol{m-1}} = (\mathbf{MP}_{m-1})^T \boldsymbol{\Lambda}(\boldsymbol{DT}_{\boldsymbol{m-1}})\mathbf{MP}_{m-1} - diag\left[(\mathbf{MP}_{m-1})^T \boldsymbol{\Lambda}(\boldsymbol{DT}_{\boldsymbol{m-1}})\mathbf{MP}_{m-1}\right]$$

$\boldsymbol{DT}_{\boldsymbol{m-1}}$ is the decision time of the first $m-1$ meetings and $\boldsymbol{\Lambda}(\boldsymbol{DT}_{\boldsymbol{m-1}})$ is an $m-1$ by $m-1$ matrix with $\boldsymbol{DT}_{\boldsymbol{m-1}}$ on the diagonal line and zeros off diagonal. In this way, *Group familiarity′$_m$* acts as a duration-weighted indicator of group familiarity and is used to check the robustness of the findings with the unweighted indicator *Group familiarity$_m$*.

Although *Group familiarity$_m$* includes the full collaboration history in the context of this committee, it does not capture the collaboration relationships among the experts outside the committee. As pointed out by Riccobono et al. (2016), collaborative experiences are highly context-specific and should be defined with respect to task and organization contexts. So we interpret *Group familiarity$_m$* as a measure of task-oriented familiarity specific to this organization context.

3.2.3. I2. Social capital centralization

According to Freeman et al. (1979), individuals' centrality indicates their power and influence in the network. This is echoed by Borgatti et al. (1998), who used degree centrality and betweenness centrality to measure the abilities to reach resources and control information flows (bridge conversations) as two facets of social capital respectively. In this light, we also measured individuals' social capital with these two centrality indicators, and similar to Mukherjee (2016), aggregate them to group-level to reflect social capital distribution in emergent group collaboration. Since we aim to examine the effects of existing social capital distribution, for each meeting m, the existing network $\mathbf{PP}_{m-1}$ was utilized to derive the degree ($\deg(j)_m$) and betweenness ($\mathrm{bet}(j)_m$) centralities of each member j. Thereafter, group social capital centralization can be calculated using the Blau's index of inequality (Reagans et al., 2004):

$$Degree\ Blau's\ index_m = 1 - \sum_{j \in V(m)} \left(\frac{\deg(j)_m}{\sum_{j \in V(m)} \deg(j)_m} \right)^2$$

$$Betweenness\ Blau's\ index_m = 1 - \sum_{j \in V(m)} \left(\frac{\mathrm{bet}(j)_m}{\sum_{j \in V(m)} \mathrm{bet}(j)_m} \right)^2$$

where $V(m)$ is the collection of the m_{th} meeting participants.

A Blau's index close to 0 indicates that a few group members' centralities are much higher than others, and social capital centralization is high in the group. Conversely, a high Blau's index close to 1 indicates decentralized social capital distribution. Based on the collaboration history ($\mathbf{PP}_{m-1}$), the two indicators reflect the extent to which there are a few dominant members, who gradually accumulated strong social capital in previous collaborations.

3.2.4. C1. Number of participants

Many OB experiment results suggest that it takes more time for a large group to reach consensus (Riccobono et al., 2016). Thus, we calculated the number of participants in each decision as a control variable, based on the **MP** matrix:

$$Number\ of\ participants_m = \sum_j \mathbf{MP}_{mj}$$

3.2.5. C2. Discipline diversity

Due to the complexity and importance of the decision problems, experts from different professional backgrounds were typically involved to integrate multidisciplinary knowledge. However, as revealed in previous studies (Bunderson, 2003; Reagans et al., 2004; van Ginkel and van Knippenberg, 2012), discipline diversity may lead to the lack of common knowledge base, and it may require more time to obtain a shared understanding on the decision problem and align different perspectives. Hence, we calculated the Blau's inequality index according to the discipline distribution of each decision group:

$$Discipline\ Blau's\ index_m = 1 - \sum_k (r_{mk})^2$$

where r_{mk} denotes the proportion of experts from discipline k in the m_{th} decision group.

According to the committee assistants, each expert is grouped into one of the three primary disciplines (i.e. structural engineering, environmental engineering and immigration management) by the committee according to their professional backgrounds. Similar to the Blau's index of social capital, a higher discipline Blau's index indicates more diverse and evenly distributed discipline backgrounds.

3.2.6. C3. Authority centralization

Numerous OB experiments found that members with authoritative identities tend to become opinion leaders, dominate in group collaboration and lead decision processes (Brockman et al., 2010; Hällgren, 2010). 34 of the 67 experts in the committee hold Chinese Academy of Science and Academy of Engineering membership, which is the most senior academic identity indicating outstanding achievements and academic authority.

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According to the committee vice chair, the opinions of Academy members (especially those with salient contributions to Program N) are more likely to be appreciated by others. Such authoritative members may dominate the group decision process and accelerate decision speed, especially in Chinese culture (Sun et al., 2008). In this light, we followed Riccobono et al. (2016) to calculate the proportion of Academy members in each decision group as an indicator of authority centralization:

$$Authority\ centralization_m = \frac{\sum_{l \in \{V(m) \cap V(A)\}} \mathbf{MP}_{ml}}{\sum_{j \in V(m)} \mathbf{MP}_{mj}}$$

where $V(m)$ is the collection of the m_{th} meeting participants; $V(A)$ is the collection of Academy members in the committee.

Generally, a small *Authority centralization$_m$* value indicates a centralized authority distribution since a small proportion of group members hold senior identities, and vice versa. However, one thing to be noted is that when *Authority centralization$_m$* equals 0, there is no Academy member of senior authority in the group, and every decision participant is of equal identity. So we reverse all 0 values to 1, the same with the situation that all decision participants are Academy members (another situation that every participant is of equal authority), to reflect fully decentralized authority.

3.2.7. C4 & C5. Decision problem type and level

The nature of a decision problem may significantly influence decision speed, so we included decision problem type and level as control variables (Beringer et al., 2013; Eweje et al., 2012). This is echoed by the committee secretary, who emphasized that the decision type and level may determine the urgency and priority of the decision problem and further influence decision speed. According to the level of the corresponding project (or program), each decision problem was classified into four categories, i.e. the whole program, channels (the major structures), auxiliary structures (e.g. small reservoir and weir) and others (e.g. equipment procurement and information system). Decisions at the level of the whole program (e.g. ecological influence of the whole program) and channels (e.g. the feasibility of changing channel routine) tend to be cautiously or even repeatedly discussed, due to the large social-environmental impacts. Auxiliary structures and other supporting systems are of smaller scales and lower importance, and the related decisions may take less time.

Considering the characteristics of hydraulic engineering projects in Program N, we classified the decisions into four types with respect to project stages, i.e. design, construction, maintenance, water resource distribution and other (may exist in all stages, e.g. immigration management, which involves relocating over 300,000 local residents in total). Since some projects in Program N are unprecedented in scale and complexity, design and construction problems stand out as prominent issues attracting much attention. For example, there were repeated discussions on the design of the Yellow River tunnel. However, other problems, such as immigration, are also non-trivial due to their profound societal influences.

Treating the “others” categories of both decision type and level as the baseline, we created a dummy variable for each of the 3 categories in decision type and 4 categories in decision level.

3.2.8. C6. Co-authorship-based familiarity indicator

In addition to the group familiarity in this context (I1), we also retrieved the experts' research papers and derived a co-authorship-based familiarity indicator to control the potential collaborations outside the committee, which may influence decision-making in this context. Similar to *Group familiarity$_m$*, the co-authorship-based familiarity indicator is calculated using the co-authorship network existing before the m_{th} meeting ($\boldsymbol{CA}_{m-1}$).[3]

$$Group\ familiarity(coauthor)_m = \frac{(p_m)^T * \boldsymbol{CA}_{m-1} * p_m}{\left[(p_m)^T * p_m\right] * \left[(p_m)^T * p_m - 1\right]}$$

3.3. Cox regression model

Since the dependent variable is the duration of decision meetings, we followed Reagans et al. (2004) to utilize Cox regression, an extension of survival analysis, to examine the effects of independent and control variables. The Cox regression model, also known as proportional hazards model, describes the probability of an event happening (i.e. reaching a decision in decision meeting) at time t as the combination of baseline level $h_0(t)$ and the effects of covariates:

$$h(t|X_i) = h_0(t)\ \exp(\beta_1 X_{i1} + \ldots + \beta_s X_{is})$$

where t is the time needed to reach a decision in this study; $X_i = \{X_{i1}, \ldots, X_{is}\}$ is the i_{th} sample.

Variables with positive coefficients are associated with higher probability of reaching a decision in the current period (instead of delaying it into the next period), so they are interpreted as contributing to timely decisions. For example, if β_1 is positive, the probability of completing the decision no later than period t grows with X_1, so X_1 is associated with more timely decision. Variables with negative coefficients, on the other hand, are interpreted as hindering timely decisions. Besides, the proportional hazard assumption of cox regression should be tested with the time-series trend of residuals (scaled Schoenfeld residuals), and a stable trend supports the validity of the assumption (Therneau and Grambsch, 2013).

4. Empirical analysis results

4.1. Dynamics in meeting-based collaboration network

The collaboration network keeps growing with each decision meeting bridging the collaborations among its participants. Based on the matrix $\mathbf{PP}_m$ (the unimodal collaboration network) after

[3] The match between the research papers to the meeting date cannot be totally exact, given that research papers are published on monthly or even yearly bases. Considering the fact that it may take a long time from starting collaboration to get published, we included all the papers published not only before but also in the year that the meeting was held to control more potential collaboration relationships.

each meeting m, Fig. 2 briefly illustrates the expansion of the collaboration network from the 10th to the 60th and 110th meetings.

Despite its continuous expansion, the collaboration network maintains a clear core-periphery structure, which was also widely observed in previous studies on collaborative decision-making (Jaber et al., 2015; Roberto, 2003). The members' network positions keep changing as the network expands, indicating the dynamics in social capital distribution. The stability of the network core indicates that some core members keep participating and maintain consistency in decision-making. The dynamic periphery consists of members who occasionally participate to contribute expertise to the decision problems specific to their domain knowledge. Compared to networks with multiple cores, this single-core structure implies better aligned objectives and less conflict in decision-making (Roberto, 2003). The effects of these network structural dynamics are further explored in the following section.

The co-authorship networks of the experts in the corresponding periods are also constructed as a control variable of the experts' collaborations outside the committee (C6) and illustrated below the meeting-based collaboration networks. As shown in Fig. 2, the co-authorship networks are much less well-connected and do not grow significantly.

4.2. Cox regression model results

Based on the methods described in Section 3.2, we calculated the dependent, independent and control variables, and the descriptive statistics and correlation matrix are shown in Table 2. Group familiarity, social capital centralization, discipline diversity and decision problem level all have moderate correlations with decision time, implying the potential effects to be examined with cox regression.

Using the R package survival (see Therneau and Grambsch, 2013 for details), we performed cox regression following the three-step procedure in Reagans et al. (2004). First, a model without any explanatory variable (equivalent to simple survival analysis) was run as the baseline (model 1). Second, only control variables were included to reveal their effects on decision time (model 2). Third, the full model (model 3) including both the independent and control variables was constructed to test the model hypotheses (Table 3).

Schoenfeld scaled residual tests were performed on model 2 and model 3, and the results support the validity of the proportional hazards assumption. The comparison between model 1 and model 2 suggests that only two control variables have marginally significant (at 0.1 level) effects on decision time. The log-likelihood ratio test further indicates that model 2, as a whole, does not have significantly better predictive power than the baseline model. Comparing model 3 with models 1 and 2, the log-likelihood ratio tests suggest that model 3 significantly outperformed the other 2 models. As a robustness test, we also estimated model 3 using the duration-weighted group familiarity as the group familiarity indicator (I1). The results of both models are illustrated in Fig. 3 for comparison. As shown in Fig. 3, the two sets of coefficients are

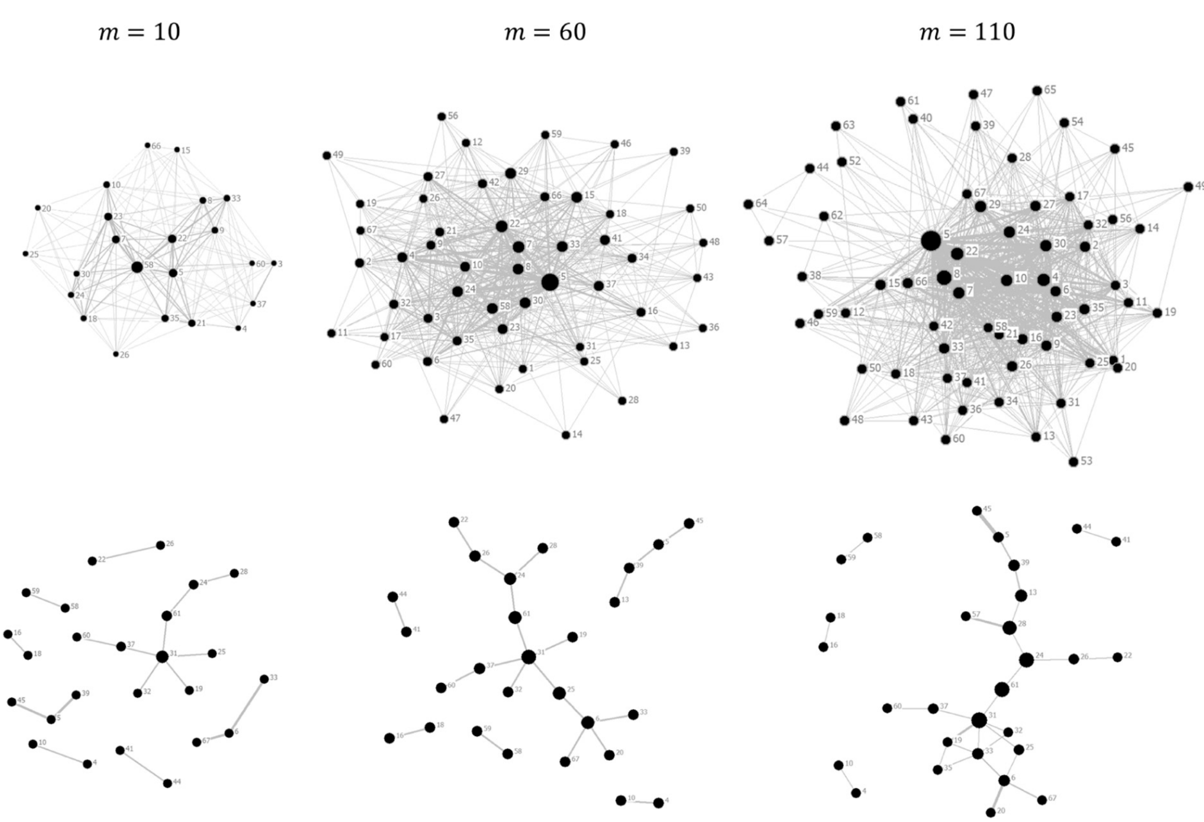

Fig. 2. The growth of the experts' meeting-based collaboration network and co-authorship network. Note: line width indicates tie strength, and node size is proportional to betweenness centrality value. The nodes are labeled consistently in the networks.

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Table 2
Descriptive statistics and correlation matrix.

Variables	Mean	SD	D1	I1	I2.1	I2.2	C1	C2	C3	C4.1	C4.2	C4.3	C5.1	C5.2	C5.3	C5.4
Decision time (D1)	3.287	2.364	-													
Group familiarity (I1)	6.339	6.593	**-0.179**	-												
Social capital centralization (I2)																
-betweenness Blau's index (I2.1)	0.683	0.185	**0.156**	**-0.182**	-											
-degree Blau's index (I2.2)	0.732	0.225	0.116	**0.228**	**0.407**	-										
Number of participants (C1)	6.172	3.020	-0.060	-0.069	**0.431**	**0.495**	-									
Discipline diversity (C2)	0.195	0.242	**0.158**	**-0.339**	**0.319**	**-0.391**	-0.146	-								
Authority centralization (C3)	0.541	0.229	-0.001	-0.058	**0.247**	**0.587**	**0.430**	**-0.300**	-							
Decision problem level dummies (C4)																
-auxiliary structure (C4.1)	0.389	0.489	-0.097	-0.145	0.088	0.108	0.067	-0.147	**0.195**	-						
-channel (C4.2)	0.172	0.379	0.131	0.026	-0.137	**-0.173**	**-0.228**	0.038	-0.094	**-0.363**	-					
-whole program (C4.3)	0.274	0.447	0.101	**0.260**	0.007	0.117	0.065	0.020	0.001	**-0.490**	**-0.280**	-				
Decision problem type dummies (C5)																
-design (C5.1)	0.274	0.447	-0.020	-0.007	0.000	0.054	-0.049	-0.049	0.040	**0.360**	0.136	**-0.281**	-			
-construction (C5.2)	0.178	0.384	0.049	-0.051	-0.013	-0.044	**-0.165**	-0.109	0.043	**0.346**	-0.036	**-0.212**	**-0.286**	-		
-structure maintenance (C5.3)	0.153	0.361	0.008	-0.026	-0.007	-0.009	**0.158**	-0.005	0.090	-0.012	-0.100	**0.176**	**-0.261**	**-0.198**	-	
-water resource (C5.4)	0.166	0.373	-0.003	**0.232**	0.000	0.127	-0.008	0.016	0.042	**-0.285**	-0.021	**0.456**	**-0.274**	**-0.208**	**-0.189**	-
Group familiarity (co-authorship, C6)	0.022	0.056	-0.088	0.024	0.134	**0.187**	**0.178**	-0.089	**0.225**	**0.194**	-0.074	-0.119	0.059	-0.073	0.091	0.013

Note: significant correlation coefficients (at $p < 0.05$ level) are denoted in **bold**.

highly consistent, and hence, the results of model 3 can be meaningfully interpreted with respect to the hypotheses.

According to the results of model 3, group familiarity (I1) has positive influence on the probability of event happening (i.e. reaching a decision), supporting Hypothesis 1. The larger the betweenness Blau's index (I2.1) (lower social capital centralization in terms of betweenness centrality), the lower the probability of reaching a decision immediately. This supports Hypothesis 2 in that more centralized social capital distribution increases the probability of making an immediate decision. The coefficient of degree Blau's index (I2.2) is however insignificant, not supporting Hypothesis 2 in terms of degree centrality. In this sense, the social capital in the form of betweenness centrality (bridging dialogs) is more influential.

To visualize the effects of each independent variable, Fig. 4 compares the estimated $S(t)$ functions (the probability of decision time exceeding t) when the variable is 0 (as the baseline level, the dashed black curve) and when it is at its median level (with the dashed grey curve showing the 95% confidence interval), holding other variables constant. The baseline $S(t)$ curves of group familiarity (I1) lies outside the 95% confidence interval of the median level, indicating that higher group familiarity significantly drives decision time down. Similarly, the baseline curve of betweenness Blau's index (I2.1) lies significantly below the median level, meaning that lower social capital centralization drives decision time up. The curves of degree Blau's index (I2.2) however do not show significant difference. Besides, two decision problem type control variables have marginally significant effects on decision time at 0.1 levels. This corroborates the fact that experts tend to discuss more on the critical decisions related to main structures (channels, C4.2) and the whole program (C4.3), and thus make decisions slower (negative coefficients).

5. Discussions

The empirical analysis results support Hypothesis 1 and partially support Hypothesis 2 in terms of the social capital reflected in betweenness centrality, and are discussed in detail as follows.

5.1. Precious but scarce collaboration experience

The empirical finding on Hypothesis 1, that the previous collaboration experience in this organization context is a significant facilitator for timely decisions, can be understood from two perspectives.

On the one hand, establishing mutual objective and psychological safety in collaborative decision groups is an essential process (Edmondson, 1999), which can be accelerated to a large extent by previous collaboration experiences. As widely reported, incongruent goals change collaborative decision-making into a prolonged bargaining process, and make the decision process two steps forward and one step back (Assaf and Al-Hejji, 2006). A lack of psychological safety hinders the integration of distributed knowledge (Edmondson, 1999). Some previous studies in project environment suggest that prior collaboration

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Table 3
Cox regression model of decision time.

Predictors	1. Baseline	2. Controls	3. Full
Independent variables			
Group familiarity (I1)			0.370 (0.170)*
Social capital centralization (I2)			
-betweenness Blau's index (I2.1)			-1.493 (0.469)**
-degree Blau's index (I2.2)			0.935 (0.816)
Control variables			
Number of participants (C1)		0.017 (0.030)	0.010 (0.047)
Discipline diversity (C2)		-0.047 (0.340)	0.666 (0.503)
Authority centralization (C3)		-0.236 (0.420)	-0.149 (0.520)
Decision problem level dummies (C4)			
-auxiliary structure (C4.1)		-0.038 (0.325)	0.094 (0.339)
-channel (C4.2)		-0.530 (0.306)†	-0.589 (0.321)†
-whole program (C4.3)		-0.504 (0.290)†	-0.531 (0.291)†
Decision problem type dummies (C5)			
-design (C5.1)		-0.014 (0.299)	-0.181 (0.317)
-construction (C5.2)		-0.218 (0.322)	-0.291 (0.337)
-structure maintenance (C5.3)		0.035 (0.293)	-0.102 (0.302)
-water resource (C5.4)		0.164 (0.276)	-0.022 (0.300)
Group familiarity (co-authorship, C6)		0.728 (1.633)	0.681 (1.597)
Log likelihood	-640.28	-634.46	-628.72
LR test against Model 1	-	11.65	23.12*
LR test against Model 2	-	-	11.47**
Sample size	157	157	157

Note: † denotes $p < 0.10$; * denotes $p < 0.05$; ** denotes $p < 0.01$; Robust standard errors are in parentheses.

and trust contribute to tackling these problems (Buvik and Rolfsen, 2015; Savelsbergh et al., 2015). This study further reveals the effect of task-oriented and context-specific collaboration experience on decision speed.

On the other hand, no team is born efficient, and there is an inevitable adaptation process for team members to develop an efficient collaboration pattern (Savelsbergh et al., 2015). Bringing unacquainted people together to compose a team is a rather time consuming task, which may delay the decision. Team members need to simultaneously tackle the challenges from both the new task and the new working constellation, making it hard to concentrate solely on the decision problem. Harrison et al. (2003) OB experiments revealed the "catch up effect" that continuous collaborations make unacquainted people gradually collaborate as efficiently as acquainted teams, while one-off teams with continuously changing members never catch up with acquainted teams. This is further substantiated by this study in a real-world project decision setting, in that familiar relationships developed via continuous collaborations improve group decision speed.

Despite the benefits of maintaining continuity in decision groups, the one-off nature of project decisions inevitably causes the scarcity of familiar collaboration relationships (Savelsbergh et al., 2015). As project-based organizing becomes increasingly prevalent, many firms are in a competition to make organization structures "fluid" with multidisciplinary temporary teams in pursuit of capability alignment. The findings of this study, however, remind us of the need for stability and familiarity in collaborative decision-making. Each project decision group is a network of collaborative members rather than a simple collection of technical knowledge (Savelsbergh et al., 2015). So involving the most knowledgeable experts does not necessarily solve decision problems efficiently, and collaboration experiences should also be considered when recruiting decision group members (Jaber et al., 2015). Therefore, for knowledge intensive project decisions with high requirements on decision speed, methods to balance the trade-off between capability alignment and collaboration experience are promising (e.g. Jaber et al., 2015).

5.2. Centralization for cohesive collaborations

According to social network theory (Freeman et al., 1979), degree centrality and betweenness centrality respectively reflect individuals' abilities to reach a wide range of information and to bridge dialogs. The empirical findings on Hypothesis 2 suggest that centralized social capital in the form of betweenness centrality has more significant influence on decision speed. In collaborative decision groups, the existence of members with superior betweenness centrality can potentially make two unique contributions to group collaboration efficiency.

First, central members have collaboration experiences with many other members, who have not collaborated before. Informed by these experiences, they are more able to develop a commonly accepted collaboration pattern, facilitate a shared understanding on the decision problem and establish a mutual objective across the group. In this sense, they contribute to improve the overall level of cohesion in the decision group (Brockman et al., 2010; Wang et al., 2005). The abundant collaboration experiences they accumulated via previous efforts can be regarded as an intangible capital enabling group efficiency improvement, which would be impossible without them.

Second, central members tend to bridge the communication between others, obtain more information and have stronger influence on others' opinions. From the theoretical lens of Transactive Memory, each pair of collaborators tends to encode a

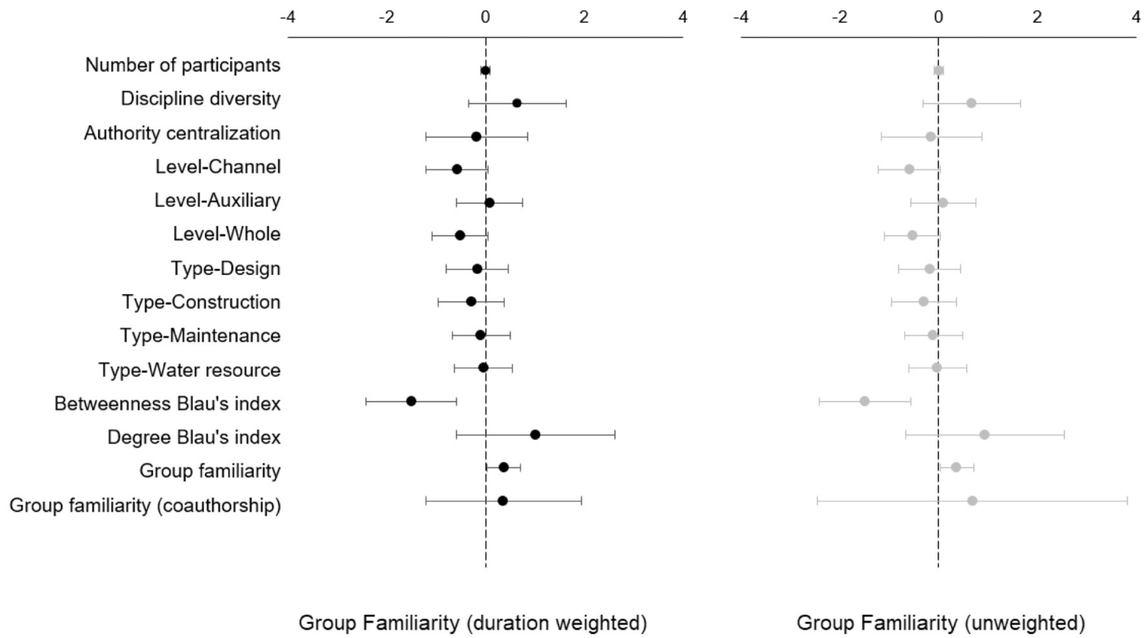

Fig. 3. Model coefficients with different group familiarity indicators.

set of Transactive Memories (e.g. code names) specific to them in order to make communication parsimonious (Hollingshead, 2001). This phenomenon is especially relevant in multidisciplinary teams, in which each discipline may have its own jargons (Bunderson, 2003). Central members' superior Transactive Memory enables them to communicate more efficiently with others. So they are both more absorptive of information from others and more persuasive to others, and hence, potentially act as the information-processing center of their groups (Bunderson, 2003; Hollingshead, 2001). Centralized team information processing has long been posited to reduce redundancy, avoid conflicts in communication, and ensure rapid diffusion of the best ideas (Crawford and Lepine, 2013). This is especially beneficial for the efficiency of project decision groups.

Just as physical capital promotes production efficiency, social capital accumulated with Transactive Memory and other forms facilitates teamwork efficiency. The empirical findings of this study corroborate this theoretical perspective in real-world project decisions and further suggest that centralized social capital distribution in groups is even more beneficial for timely decision-making. The findings also partly explain why staff turnover and job rotation can have a wide influence on other team members' collaboration, and it may take a long time for the team to recover and re-accumulate social capital. This reminds managers to be particularly cautious when moving the central members of teams.

Arguably, social power centralization may make group decisions heavily dependent on the dominant members. In portfolio or organizational decision-making, many researchers frequently attributed various decision errors (such as illusion of control (Stingl and Geraldi, 2017), over-optimism bias (Lechler and Thomas, 2015), top managements' pet project

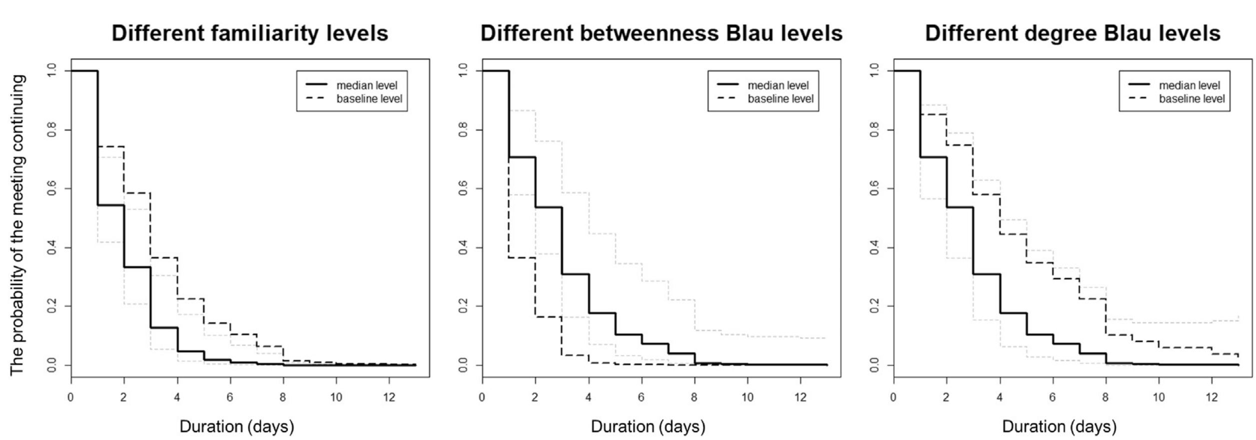

Fig. 4. Survival functions at different levels of independent variables.

(Beringer et al., 2013) and groupthink (Hällgren, 2010)) to high authority and power centralization. On the other hand, many other studies point to the positive side of having strong leadership in decision-making (van Ginkel and van Knippenberg, 2012; Wang et al., 2005), and the net effect of social power centralization remains controversial. In fact, the social power in team collaboration has multiple facets, such as higher organization hierarchy, technical authority, and relational leadership (Kurvers et al., 2015). The mixed empirical evidences in previous studies partly ascribe to the difficulty in isolating the effects of various types of social power, which may have rather different effects (Bergman et al., 2012). The empirical setting of this study is ideal for examining the effects of relational leadership, since there is no explicitly defined organization hierarchy in the expert committee, and the effects of technical authority are controlled. The findings support the positive effects of relational leadership on decision speed. Compared to the leadership behaviors based on formal hierarchy and authoritative identity, relational leadership is inherently emergent and rotational (Kurvers et al., 2015). As pointed out by Gloor (2016), the spontaneous emergence of relational leaders reflects a team's adaption to its task and environment, and leadership rotation further facilitates balanced contributions of different members. Relational leadership and leadership rotation are efficiency-oriented and act as the honest signals of effective teamwork (Gloor, 2016). Recently, many project management schemes, that weaken formal leadership but encourage relational and rotational leadership, have been prevalent (e.g. agile project management (APM) in IT industry and integrated project delivery (IPD) and the Last planner system in construction industry). The advantages of the schemes demonstrate the benefits of relational and rotational leadership in enhancing multidisciplinary resources integration and enhancing project teams' responsiveness to dynamic environment.

6. Conclusions and future studies

Using the longitudinal data of the expert committee's 157 decision meetings, this study reveals the effects of collaborative network dynamics on group decision speed. The analysis results suggest that higher group familiarity and social capital centralization contribute to higher decision speed. The findings generate implications for both theory development and decision management practices.

From the theoretical perspective of social network theory, this study substantiates the positive effects of network tie strength (familiarity) and network position strength (centrality) in a real-world project decision setting. The findings heed the call for investigating the behavioral dimension of project decision-making (Bakht and El-Diraby, 2015; Stingl and Geraldi, 2017) and lay the foundation for further studies on collaborative decision-making in PBO. Moreover, this study also acts as a call for the cross-fertilization between OB and project management fields.

For decision management practice, the findings suggest the relational dimension to be considered beside capability alignment when recruiting decision group members. A decision group with the most knowledgeable experts does not ensure a timely solution to decision problems. The previous collaboration experience among participants is also a necessary facilitator of decision efficiency. Besides, including members with strong social capital in decision groups can also serve as the "lubricant" of teamwork that bridge communications and improve team efficiency. Therefore, staffing a decision group is a non-trivial task that cannot be performed simply based on technical expertise alignment. In one-off project decisions under dynamic environments, reasonable efforts should be taken to maintain continuity and encourage relational leadership in collaborative decision groups.

The findings of this study should be viewed with respect to its context and limitations. First, the empirical data come from one industry in a single country. Although Program N includes nearly all recent large-scale water transfer projects in China, caution should still be taken when generalizing the findings to other organization contexts. Future studies can further explore the effects of collaboration dynamics on decision efficiency in different contexts (e.g. organization culture, industry sector, etc.). Such organization context variables may also act as moderators of the revealed effects. Second, due to the limitation in data availability and difficulty in objective measurement, decision quality is not considered in empirical analysis. According to our interview findings, this limitation is alleviated to a large extent in this empirical setting since most expert committee's decisions turn out to be of high quality in practice. Following the logic of this study, future studies can further examine the effects of collaboration network dynamics on decision quality in other organizations. Third, the data do not capture the actual interactions among experts during the meeting and the centrality indicators should be interpreted as potential social power, which the experts may not utilize in decision processes. This does not contradict the research purpose of studying long-term collaboration network dynamics and the application purpose of enabling timely decisions with adequate decision group design. However, more information on the actual decision process is invaluable to open the black box of the behavioral dimension of collaborative project decision-making.

Conflict of interest

The authors declare that there are no conflict of interest.

Acknowledgments

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