INTRODUCTION

Modern supply chains (SCs) are prone to disruptions and usually, at some point, warnings about potential or upcoming problems occur (Bode et al., 2011; Craighead et al., 2007). More specifically, prior to an SC disruption, a trail of early warnings usually signals their likelihood, enabling firms to reduce a problem’s impact or even avoid it entirely, so that firm performance is not negatively affected. Such SC disruption warnings convey information about problems that may disturb the up- or downstream flow of goods and materials (Bode et al., 2011; Bundy et al., 2017). Examples include warning messages about machine inconsistencies, personnel strikes, weather alerts, or criminal activities, which may threaten the firm’s performance through their potential to delay production or the shipment of materials. Firms may encounter several such warnings about different functions simultaneously (e.g., transportation, production, or purchasing), as they are normally involved in dozens of SCs in different geographical areas.

Abstract

Firms can adopt several strategies to increase their robustness to potential supply chain (SC) disruptions. One promising strategy is the use of a cross-functional team with representatives from functional departments. Such a team may facilitate sharing relevant information, enabling the firm to respond effectively to SC disruption warnings. However, despite their potential, cross-functional teams also differ in their ability to respond to SC disruption warnings and to ensure firm robustness. Extending insights from information-processing theory and team research to the field of SC management, we propose that a cross-functional team’s ability to handle high numbers of SC disruption warnings depends on the extent to which the team adopts centralized decision-making, with one or two members orchestrating the decision-making process. We also introduce internal integration problems as a mediating mechanism explaining why a cross-functional team lacking centralized decision-making may be unable to handle high numbers of SC disruption warnings. In two independent studies, we use multi-source data on cross-functional teams’ performance in dealing with SC disruption warnings during a realistic SC management simulation; the results support our predictions.

KEYWORDS

cross-functional teams, decision-making, internal integration, organizational information-processing theory, robustness, supply chain disruption warnings
Firms’ interpretation of SC disruption warnings and their implementation of precautionary measures strongly determine firm robustness, that is, the ability to maintain performance despite internal or external disruptions (Brandon-Jones et al., 2014). To enhance firm robustness, it has been suggested that organizations should establish cross-functional teams comprising managers from different functional departments within the firm (Blackhurst et al., 2011; Durach et al., 2015; Poberschnigg et al., 2020). Poberschnigg et al. (2020), for example, suggested that cross-functional integration can support organizations’ risk management capabilities. However, to the best of our knowledge, there is no empirical SC research on the usefulness of cross-functional teams for effectively handling SC disruption warnings. Moreover, empirical studies in cognate research areas have painted an inconsistent picture. For example, team effectiveness research has found that some cross-functional teams may effectively handle non-routine events and contingencies, while others may experience internal integration problems due to the difficulties of processing large amounts of information within limited time frames (e.g., Ellis, 2006; Salas et al., 2000; Uitdewilligen & Waller, 2018). Combined, the lack of SC research on cross-functional teams and mixed findings from related research fields highlight the need for in-depth investigation of when and how a firm’s cross-functional team may help to handle uncertainties caused by SC disruption warnings and, in turn, enhance firm robustness.

We conduct such an investigation and leverage organizational information-processing theory (OIPT; Bode et al., 2011; Galbraith, 1974) as an appropriate conceptual perspective on how firms cope with information-processing demands amid the uncertainty of non-routine events such as SC disruption warnings. In two quantitative empirical studies, we collected multi-source, multi-informant data from a SC management simulation that used a four-person cross-functional team to deal with SC disruption warnings. Our findings suggest that the information-processing demands associated with increased numbers of SC disruption warnings may inhibit a cross-functional team from ensuring its firm’s robustness. Extending insights from group information-processing theory (Hinsz et al., 1997) to the SC domain, we further find that centralized decision-making by one or two team members enables the firm’s cross-functional team to better handle the information-processing demands of multiple simultaneous SC disruption warnings. Moreover, we identify internal integration problems as a mediating mechanism that explains the conditional relationship between the information-processing demands of SC disruption warnings and firm robustness.

These results show that simply implementing a cross-functional team is insufficient to make a firm robust, as the team’s effectiveness in handling SC disruption warnings may depend on its internal decision-making structure and integration. Managers can use our insights to better structure decision-making processes in the cross-functional team to, ultimately, increase firm robustness when facing serious SC threats. Theoretically, our findings illustrate how macro-level insights from OIPT and micro-level insights from team research can be integrated, thereby opening up new conceptual perspectives for interdisciplinary research on firm robustness and SC management (Bendoly et al., 2006; Fahimnia et al., 2019).

THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

Heeding supply chain disruption warnings: an information-processing perspective

Firms managing risks and dealing with SC disruptions can aim for robustness and/or resilience (Brandon-Jones et al., 2014), which respectively refer to proactive and reactive strategies. While both are generally needed, we focus on robustness. Robust firms proactively avoid or resist negative performance impacts of an SC disruption (Durach et al., 2015; Vlajic et al., 2012). To do so, such firms aim to remove the root cause of the SC risk (Durach et al., 2015) or nullify its probability of impact (Hajmohammad & Vachon, 2016). Examples include changing suppliers or increasing safety stock (Jüttner et al., 2003; Manhart et al., 2020).

To ensure robustness, a firm needs to respond to warnings that indicate the risk of an SC disruption. Such disruption warnings are broadly defined as signals of unexpected or unwanted change to normal system behavior that cause or have the potential to cause a loss (Cooke & Rohleder, 2006). They provide a firm with time to analyze information about the threat and to arrange precautionary measures so that the SC disruption can be appropriately managed to avoid a negative impact on performance (Bode & Macdonald, 2017; Ellis et al., 2011; Manhart et al., 2020). For example, a warning of severe weather will give a firm time to build up additional stock to cope with potential delays in supply from an affected area or to find alternative transportation routes without suffering performance losses, thereby being robust.

One influential perspective on how a firm may effectively use information about SC disruption warnings to build robustness stems from OIPT (Galbraith, 1974; Tushman & Nadler, 1978). OIPT’s central tenet is that, for optimal decisions, a firm should match its information-processing capacity to the uncertainty and associated information-processing demands it faces in the environment. Environments with many non-routine events create more uncertainty and, therefore, require the sharing and interpretation of larger quantities of information to derive countermeasures, compared to environments with predominantly routine events (Galbraith, 1974). When dealing with well-understood, routine events, OIPT suggests
that hierarchical referral and standardized vertical information systems may suffice to process information and decide on firm activities. However, with increasing numbers of non-routine events, more advanced systems are needed, and OIPT suggests the importance of structural solutions that promote personal and lateral relationships among the functional departments within the firm.

One prominent lateral structural solution is to use a cross-functional team, which may be a permanent part of the organization or activated temporarily for a specific situation. In either case, using such a team has been proposed to enhance an organization’s risk management capabilities because a possible SC disruption in one functional area may also have implications for other functional areas (Blackhurst et al., 2011; Poberschüng et al., 2020). Therefore, it is important that relevant disruption warning information is shared among different functional managers so that integrative solutions can be formulated to prevent problems that may affect firm performance (Durach et al., 2015). A cross-functional team can operate at different levels, including the production shop floor and middle- or higher-level management. In the present research, a cross-functional team comprises higher-level managers of different departments who represent the firm as a whole and make key decisions (e.g., set up supplier contracts and invest in machines).

The effectiveness of cross-functional teams in ensuring firm robustness

The moderating role of team decision-making centralization

OIPT suggests the relevance of a cross-functional team for handling the uncertainty associated with non-routine situations. However, evaluations of several disruptions indicate that even a cross-functional team may struggle to handle larger numbers of warnings (DeChurch & Zaccaro, 2010; Ellis, 2006; Salas et al., 2000). In such cases, information-processing demands become too high for a team and accumulated warnings result in a “quantity-induced crisis” that “creates a vicious cycle of ... declining performance” (Rudolph & Repenning, 2002, p. 25). Based on OIPT, we suggest that such detrimental effects are particularly likely to emerge in a cross-functional team incapable of efficiently integrating scattered information about the potential impact of SC disruptions and of maintaining structure and oversight during subsequent decision-making (Galbraith, 1974). Without such information-processing capacities, each member must invest finite time and attention in collecting and interpreting relevant information to ensure that the team makes well-informed decisions on how to handle imminent disruptions (Davison et al., 2012). Dealing with high information-processing demands in the form of multiple SC disruption warnings will, therefore, be highly challenging for a cross-functional team incapable of efficiently integrating information and maintaining oversight during decision-making.

As OIPT neither specifies the internal dynamics that may shape cross-functional teams’ ultimate effectiveness nor considers or identifies what factors may explain the different information-processing capacities among these teams, we integrate OIPT with conceptual insights from group information-processing theory (GIPT; Crawford & LePine, 2013; Hinsz et al., 1997; Humphrey & Aime, 2014). GIPT submits that a team’s ability to integrate scattered information is shaped by the interaction patterns among team members during decision-making (Duncan, 1974; Kuvaas, 2002). Drawing from these insights, we propose that a more centralized decision-making structure enables a cross-functional team to maintain oversight when making decisions using larger amounts of scattered information. A team with a more centralized decision-making structure relies on one or two central members to lead and act as intermediaries, orchestrating all decision-making in response to warnings on behalf of the whole team (Hollenbeck et al., 2010). The central members are, thus, uniquely positioned to efficiently access and integrate the information held by different team members on warnings, thereby forming a “big picture” understanding of the firm’s overall SC (Davison et al., 2012, p. 4; see also: Klein & Pierce, 2001). Central members can further communicate this big-picture understanding to ensure that team members’ decisions on countermeasures are based on complete information (de Vries et al., 2016). By contrast, in a team with a less centralized structure, members have equal roles in decision-making and, therefore, lack the central members to efficiently access and integrate different team members’ information (Tröster et al., 2014).

Based on our combination of OIPT and GIPT, we suggest that the team-level information-processing capacities examined in GIPT may be particularly important in ensuring firm robustness when teams face higher information-processing demands, as suggested in OIPT. A more centralized team can quickly and efficiently prepare for a disruption by integrating large quantities of information (Davison et al., 2012; Tröster et al., 2014) and may, therefore, be less likely to systematically overlook or ignore information associated with accumulated SC disruption warnings. This, in turn, increases the likelihood that the team will decide on effective countermeasures that prevent many simultaneous SC disruptions negatively impacting on performance, thereby mitigating the negative relationship between information-processing demands stemming from the number of SC disruption warnings and firm robustness. In contrast, a cross-functional team with more decentralized decision-making lacks the capacity to efficiently integrate larger quantities of information, causing its
members to revert to the natural tendencies that prevent them maintaining oversight of the situation (Cronin & Weingart, 2007). Such teams are, thus, less able to prepare for and avoid or resist the performance impacts of actual disruption, which may ultimately prevent them mitigating the relationship between information-processing demands and reduced firm robustness.

**H1** The relationship between information-processing demands (i.e., the number of SC disruption warnings) and firm robustness is moderated by the centralization of decision-making in the firm’s cross-functional team. This negative relationship is mitigated when decision-making centralization is higher but strengthened when decision-making centralization is lower.

The mediating role of internal integration problems

Supply chain research suggests that firms may facilitate risk management via improved coordination and effective and efficient flows of information, materials, and decisions across functional departments (i.e., internal integration; Durach et al., 2015; Manhart et al., 2020; Poberschnigg et al., 2020). Within firms using a cross-functional team to manage SC disruption warnings, such internal integration should be achieved through alignment between managers within the team. Correspondingly, we propose that the extent to which a cross-functional team experiences internal integration problems is an important mediator of the moderated relationship outlined in H1.

When internal integration problems occur, a firm’s cross-functional team members unwittingly counteract, rather than support and supplement, one another’s actions, resulting in redundancy and wasted resources (Poberschnigg et al., 2020; Schoenherr & Swink, 2012; Williams et al., 2013). Such problems are especially likely to emerge when the cross-functional team has high information-processing demands due to multiple SC disruption warnings, which may cause information overload in preparing for SC disruptions and prevent members from integrating their efforts. Importantly, however, we predict that SC disruption warnings will only translate into internal integration problems when the cross-functional team’s capacities are surpassed by their information-processing demands (Flynn et al., 2016; Williams et al., 2013). That is, integration problems surface when a cross-functional team lacking a centralized decision-making structure faces multiple SC disruption warnings (Lanaj et al., 2013). In such situations, managers are more likely to focus on information closest to their immediate work domain and may overlook warnings in other domains that may impact their function (Baddeley, 1972; Miller, 1978). When preparation measures in response to SC disruption warnings are not aligned, the cross-functional team, as a whole, may encounter internal integration problems.

A team may prevent internal integration problems by using a more centralized decision-making structure to handle increased information-processing demands. Central actors are uniquely positioned in the team to efficiently integrate disparate information on different SC disruption warnings and may use these insights to guide joint decision-making (Davison et al., 2012; de Vries et al., 2016). These individuals can ensure that functional managers in the team integrate their unique insights on SC disruption warnings and rely on this integrated perspective to devise holistic preparation countermeasures for the firm as a whole. Therefore, we expect that functional managers in a cross-functional team are unlikely to pursue conflicting actions in their handling of multiple SC disruption warnings when joint decision-making is overseen and guided centrally.

**H2** The relationship between information-processing demands (i.e., the number of SC disruption warnings) and internal integration problems is moderated by the centralization of decision-making in the firm’s cross-functional team. This positive relationship is mitigated when decision-making centralization is higher but strengthened when decision-making centralization is lower.

We further predict that internal integration problems will lead to higher performance impacts of the actual disruption and, therefore, reduce firm robustness. When such problems occur, members of the firm’s cross-functional team engage in preparatory actions that undermine one another’s efforts (Schoenherr & Swink, 2012; Williams et al., 2013), and are less likely to develop internally integrated countermeasures that enable firm robustness (Brandon-Jones et al., 2014). Also, it takes significant time and effort to resolve internal integration problems—time that cannot be spent developing countermeasures. When internal integration problems emerge, members of a firm’s cross-functional team are, thus, unlikely to efficiently use their varied information (Oliva & Watson, 2011), so firm robustness is likely to decrease.

**H3** There is a negative relationship between a cross-functional team’s internal integration problems and firm robustness.

Our combined reasoning suggests that the conditional relationship between information-processing demands (i.e., number of SC disruption warnings) and firm robustness (i.e., change in firm performance due to SC disruption impact) is mediated by internal integration problems within the firm’s cross-functional team. Specifically, we suggest that the
number of SC disruption warnings is negatively related to firm performance if the firm’s cross-functional team relies on less centralized decision-making and that this negative relationship is dampened when the team uses more centralized decision-making. In a less centralized team facing multiple SC disruption warnings, information-processing needs and capacity are mismatched, resulting in internal integration problems that prevent the team from maintaining firm performance when an SC disruption strikes. Conversely, in a more centralized team facing increased information-processing demands, internal integration problems are less likely to surface, thereby enhancing firm robustness (see Figure 1).

H4 The interactive relationship between information-processing demands (i.e., the number of SC disruption warnings) and the cross-functional team’s decision-making centralization on firm robustness is mediated by the team’s internal integration problems.

METHODOLOGY

Since it is unlikely that any real firm would let us intentionally disrupt its SC, we used data from a highly realistic yet relatively controlled SC management simulation, called “The Fresh Connection” (TFC), to study a large number of comparable cross-functional teams’ responses to SC disruption warnings. TFC is used as an experiential learning tool in well-known companies (e.g., Heineken, Adidas, Toyota, Coca-Cola) and universities. Previous research shows its suitability for behavioral team research (e.g., Brazhkin & Zimmerman, 2019; Phadnis & Caplice, 2013) as “the decision data from the game provide a wealth of information about team behavior over time, which can be used for research on, for example, issues that relate behavior to performance criteria” (de Leeuw et al., 2015, p. 374).

We tested our hypotheses in two studies using TFC, as replicating findings in different studies increases confidence in the pattern of results (Eden, 2002). Study 1 tested H1 by examining professionals, while Study 2 aimed to replicate the Study 1 findings in a different sample and to examine the mediating role of internal integration problems (i.e., H2–H4). Eden (2002, p. 842) recommends “increas[ing] the value of the replication by investigating whether the hypothetical relationships are robust across variations in the method of empirical observation.” Accordingly, Study 2 involved alterations to several aspects of the Study 1 methodology. First, whereas Study 1 focused on between-team differences (i.e., examining why some teams are more capable of ensuring firm robustness than others), Study 2 focused on within-team differences (i.e., examining why a specific team is more capable of ensuring firm robustness in some SC simulation rounds than in others). Second, Study 2 exposed teams to internal and external SC disruption warnings, whereas teams in Study 1 only encountered external warnings. Finally, we increased the number of simulation rounds from three (Study 1) to six (Study 2) to investigate within-team differences in firm robustness across more data points.

STUDY 1

Sample and procedure

Due to time and budget constraints, we did not obtain a representative sample from the entire population of professionals working in SC management (our population of interest). Instead, we collaborated with a consultancy company and collected data from a smaller (convenience) subpopulation of professionals that participated in a global SC management challenge using TFC. We selected this subpopulation because it comprises diverse professionals from different companies, industries, and SC occupations, which has been suggested to support the external validity of research findings (Mutz, 2011; Scandura & Williams, 2000). The consultancy company organizing the global SC management challenge allowed us to send a short survey to the members of 100 randomly selected teams, in return for providing feedback.
Usable data were received from a final sample of 71 teams. To assess whether this sample is representative of the sub-population, we collected additional demographic information on the subpopulation and compared that information with the demographic characteristics of our final sample (Halbesleben & Whitman, 2013). On average, individuals in our sample had 9.57 years of professional work experience ($SD = 9.72$) and had worked in 3.65 different jobs during their career ($SD = 1.38$); 26% of respondents currently held a managerial job. On average, 26% of team members were female ($SD = 24.36$). The subpopulation did not differ substantially from our final sample in terms of professional work experience ($M = 8.46, SD = 8.63$), number of jobs ($M = 3.62, SD = 1.41$), percentage of members currently holding a managerial job (23%), or percentage of female team members ($M = 31.06%, SD = 29.89$). These findings indicate that our sample was sufficiently representative of the subpopulation (Halbesleben & Whitman, 2013).

During the global SC management challenge, professionals participated in TFC and formed four-person teams that assumed the role of a higher-management cross-functional team in different fresh juice manufacturing companies. The teams comprised four roles: sales, operations, SC, and purchasing. The sales manager made decisions on delivery terms with the company’s customers (e.g., category selection, service levels, shelf life, and payment terms); the purchasing manager decided on supplier contract terms (e.g., delivery window, supplier choice, and quality controls). The operations manager handled the company’s production facilities and warehouses (e.g., number of pallet locations, shifts, and intake time); the SC manager decided on inventory and SC strategies (e.g., safety stock, lot sizes, and production interval).

Participants were randomly assigned to teams by the consultancy company organizing the SC management challenge, but they could discuss and decide within their team who would take on which role. This enabled them to assume roles that aligned best with their expertise and professional backgrounds. There were no formal power differences in teams (i.e., all roles had the same formal rank). Team members could communicate freely with one another and decide how to structure decision-making. Participants paid entry fees and had incentives to perform well.

Teams participated in three sequential TFC simulation rounds (each representing six months within the virtual company), with equivalent procedures and consistent task difficulty across teams. Teams played each round simultaneously and had two weeks to complete each round. Simulation rounds were designed to be independent, such that operational decisions made by a team in a previous round could be revised or consciously changed to avoid unduly influencing performance in subsequent rounds. This also means that if teams decided not to make any changes, the settings from the previous round would remain.

Following recommendations by Ketokivi and McIntosh (2017), we used a longitudinal, multi-source, multi-method data collection strategy in Study 1. For each of the three simulation rounds, we obtained objective log files on the number of SC disruption warnings and performance outcomes for each team. We combined these objective data with survey responses from multiple informants per team to further reduce common method bias (Flynn et al., 2018; Ketokivi & Schroeder, 2004). Specifically, after completing the third and final simulation round, all participants were prompted by the simulation software to complete an online survey focused on decision-making in their team during that round. Participation in the survey was voluntary. Because the third simulation round was the only round for which we could collect data on all the study variables, we focused on this round to test our hypotheses.

**Measures**

**Number of supply chain disruption warnings**

At the beginning of the second and third simulation rounds, teams had to deal with SC disruption warnings about potential adverse events (i.e., pirate attacks on cargo ships) if the supply of raw materials to its firm was endangered given current decision settings in the simulation (e.g., choice of suppliers). Teams received these SC disruption warnings in the simulation’s “risk map” and via an email:

A large number of freighters have recently been hijacked by Somali pirates in the Gulf of Aden. While we don’t own any cargo ships, there is a good chance that some of our suppliers use this well-known trade route. If we don’t take any action, and one of the ships from a supplier is hijacked for a number of weeks, then we could find ourselves without stock. I believe we must do something about the situation!

If not properly addressed, such threats became actual SC disruptions in subsequent rounds of the simulation, thus negatively affecting firm performance due to missing raw materials for production. Teams did not know upfront that warnings would always translate into disruptions if left unaddressed. Instead, they were provided with a probability of occurrence (i.e., once a year) on the risk map, based on which they had to decide whether to act upon the warning. Also, teams were informed of the potential impact of the SC threats (50% longer delivery lead-time) on the risk map, but they were not directly
informed of how that potential impact of SC disruptions would translate into lowered firm performance, as this was contingent on teams’ investment, supplier, and inventory decisions. Therefore, teams had to develop actions considering both the potential impact of SC threats and their own prior decisions.

All teams received the same type of SC disruption warnings with the same potential impact, as there was only one type of SC disruption warning included in the Study 1 simulation (i.e., pirate attacks on suppliers’ transport routes). Also, SC disruption warnings were sequenced and timed consistently for all teams, appearing at the start of rounds 2 and 3. If left unaddressed, SC threats appearing in round 2 affected firm performance at the end of rounds 2 and 3, while round 3 SC threats affected round 3 firm performance. Hence, there was no variance in the timing, sequence, or content of the SC warnings received by teams.

Teams did, however, differ in how many SC disruptions warnings they faced in the SC management simulation, depending on which suppliers they used, and we used this variance to capture our key study variable “number of SC disruption warnings.” Specifically, the simulation developers randomly decided on SC threats in different regions that were programmed into the game. Teams with multiple suppliers in these affected regions had to handle increased numbers of SC disruption warnings at the start of the second and third simulation rounds. Teams receiving multiple warnings faced severe information-processing demands in the simulation (Rudolph & Repenning, 2002), as they had to decide on all kinds of operational issues at the time they received the SC disruption warnings. Other teams, by contrast, encountered fewer SC disruption warning because they had no or only a single supplier in affected regions. We focused on the accumulated number of SC disruption warnings received by each team in the third and final simulation round to capture our independent variable (range: 0–4).

Decision-making centralization

After the final simulation round, we asked each participant to identify who had controlled decision-making in their team, using three items from Carter et al. (2014). For each team, we then calculated the extent to which some central members controlled decision-making using the “group degree centralization index” (Wasserman & Faust, 1994, p. 180). Drawing from prior research on small teams (Sparrowe et al., 2001; Tröster et al., 2014), we selected the group degree centralization index because it considers (a) the number of individuals that take control in decision-making, and (b) the amount of control that these central individuals exert. As such, the group degree centralization index recognizes important differences in centralization even among small teams with an equal number of central members, because these teams’ central members may differ in the amount of control they exert during decision-making (Everett & Borgatti, 1999). The exact items and procedure used for calculating decision-making centralization are provided in Appendix S1.

Firm robustness

Robustness conceptually refers to a firm’s ability to resist a negative change in performance when facing SC disruptions (Vlajic et al., 2012). We operationalize this as the degree to which a cross-functional team avoided a negative change in its firm’s ROI due to the occurrence of an SC disruption by effectively handling SC disruption warnings. ROI represents the ratio of gross revenue minus indirect costs over investments and was calculated by the simulation system. It is a well-recognized measure for financial business performance (Flynn et al., 2010; Manhart et al., 2020; Zimmermann & Foerstl, 2014), and a critical measure for organizations to understand the conditions under which a strong return can be achieved (Brandon-Jones et al., 2014). To capture a team’s ability to maintain stable ROI scores despite adverse circumstances, we used a time-series approach to determine a firm’s baseline ROI trend over simulation rounds 1–3 (Heck & Thomas, 2015) and, subsequently, to assess whether that firm’s team could avoid a change from that baseline when facing potential SC disruptions. This provides a more complete and reliable view of robustness compared to other methods that look, for example, at changes in the ROI between two consecutive rounds. Appendix S1 and S2 detail the ROI calculation and the time-series approach we used for calculating robustness based on ROI.

Control variables

As recommended by Wasserman and Faust (1994), we controlled for decision-making density when testing our predictions regarding centralization. In our case, decision-making density indicates the overall degree to which team members orchestrated direction setting, coordination, and information exchange during decision-making. We calculated the density of a team’s decision-making by dividing the sum of nominations in the team by the maximum possible number of nominations, using the group degree density index (Wasserman & Faust, 1994). Prior research has further indicated that experience differences may explain why some teams are more effective than others and, correspondingly, that it is important to control for between-team differences in experience when predicting team outcomes (Bunderson & Sutcliffe, 2002; de Vries et al., 2016). Therefore, we controlled for team members’ average years of work experience, their average number of jobs held in the past (breadth of experience), and the percentage of team members who held management positions (managerial experience).
Data analysis

Because we obtained independent observations of each team during a single simulation round, assumptions of the non-independence of data are not violated, and ordinary least squares (OLS) multiple regression analyses are appropriate to test our hypotheses (Heck & Thomas, 2015; Snijders & Bosker, 1999). We tested our conceptual model in three OLS steps. In step 1 of the analysis, we added the first-order autoregressive coefficient that reflects teams’ baseline ROI trends over simulation rounds 1–3 to model firm robustness (see Appendix S3 for details) and also included covariates. In step 2, we added the main effects of the number of SC disruption warnings and decision-making centralization. In step 3, we added the interactive term SC disruption warnings × decision-making centralization. We assessed the significance of the interactive term and the change in the adjusted R-square between steps 2 and 3. We also calculated simple slopes (Cohen et al., 2003) for the relationship between our predictor and outcome variables at high and low levels of our moderator variable (i.e., one standard deviation above and below the mean).

We grand-mean centered all predictor variables before performing the analyses (Cohen et al., 2003).

Results

Descriptive statistics

Means, standard deviations, and bivariate correlations for study variables are reported in Table 1. As explained in Appendix S3, we modeled robustness as the change in firm performance between rounds, rather than observing it directly, so firm robustness could not be included in Table 1.

Hypotheses tests

H1 suggests that the relationship between the number of SC disruption warnings and firm robustness is contingent on decision-making centralization. In line with our expectations, we found a significant interactive relationship between the number of SC disruption warnings, the centralization of decision-making, and firm robustness ($B = 97.81, SE = 27.77, p < 0.01; \text{see Table 2, Model 3}$). Moreover, the adjusted R-square of the regression model improved when we added the interaction term to the regression equation (R-square change = 0.10, $p < 0.01; \text{see Table 2, Model 3}$). Following Cohen et al. (2003), we graphically explored this interaction effect (see Figure 2) and examined the significance of the simple slopes. Figure 2 shows that the number of SC disruption warnings was unrelated to changes in firm ROI scores when the cross-functional team had high decision-making centralization (relationship at $+1SD = 6.50, SE = 5.00, n.s.$) but significantly related to declines in firm ROI scores when the team had low decision-making centralization (relationship at $-1SD = -17.43, SE = 4.99, p < 0.01$). These results indicate that cross-functional teams with a centralized decision-making structure were able to preserve their firms’ ROI when confronted with larger numbers of SC disruption warnings (i.e., higher robustness). By contrast, teams with less centralized decision-making suffered a decline in their firms’ ROI when faced with larger numbers of SC disruption warnings (i.e., lower robustness). Thus, H1 was supported.

In addition to our main hypothesis test, we also explored and confirmed the statistical robustness of our findings in supplementary analyses. The results are presented in Appendix S4.

<table>
<thead>
<tr>
<th>Variables</th>
<th>$M$</th>
<th>$SD$</th>
<th>$r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ROI (T1)</td>
<td>11.78</td>
<td>7.68</td>
<td></td>
</tr>
<tr>
<td>2 ROI (T2)</td>
<td>$-10.99$</td>
<td>33.28</td>
<td>0.17</td>
</tr>
<tr>
<td>3 ROI (T3)</td>
<td>3.29</td>
<td>42.36</td>
<td>0.33** 0.58**</td>
</tr>
<tr>
<td>4 Average experience</td>
<td>9.76</td>
<td>6.12</td>
<td>0.02</td>
</tr>
<tr>
<td>5 Breadth of experience</td>
<td>3.63</td>
<td>0.77</td>
<td>0.11</td>
</tr>
<tr>
<td>6 Managerial experience</td>
<td>0.26</td>
<td>0.27</td>
<td>$-0.12$</td>
</tr>
<tr>
<td>7 Decision-making density (T3)</td>
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<td>0.18</td>
<td>0.20</td>
</tr>
<tr>
<td>8 Decision-making centralization (T3)</td>
<td>0.18</td>
<td>0.12</td>
<td>0.09</td>
</tr>
<tr>
<td>9 Number of SC disruption warnings (T3)</td>
<td>0.89</td>
<td>0.92</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Note: $T =$ Time, SC = Supply Chain. $N =$ 71 Cross-functional Teams.

*p < 0.05.

**p < 0.01.
TABLE 2  Study 1 – Number of SC Disruption warnings, decision-making centralization, and firm robustness

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.27</td>
<td>3.29</td>
<td>4.75</td>
</tr>
<tr>
<td>Autoregressive coefficient</td>
<td>0.36 (0.07)**</td>
<td>0.36 (0.07)**</td>
<td>0.40 (0.07)**</td>
</tr>
<tr>
<td>Average experience</td>
<td>−0.74 (0.61)</td>
<td>−0.65 (0.61)</td>
<td>−0.46 (0.59)</td>
</tr>
<tr>
<td>Breadth of experience</td>
<td>9.26 (4.69)</td>
<td>9.41 (4.66)</td>
<td>7.08 (4.55)</td>
</tr>
<tr>
<td>Managerial experience</td>
<td>−13.43 (13.00)</td>
<td>−12.87 (13.00)</td>
<td>−7.04 (12.68)</td>
</tr>
<tr>
<td>Decision-making density</td>
<td>37.54 (19.09)</td>
<td>53.14 (20.54)**</td>
<td>48.44 (19.91)†</td>
</tr>
<tr>
<td>SC disruption warnings (SDW)</td>
<td>−5.49 (3.78)</td>
<td>−5.46 (3.66)</td>
<td>−5.46 (3.66)</td>
</tr>
<tr>
<td>Decision-making centralization (DMC)</td>
<td>43.43 (29.62)</td>
<td>43.64 (28.66)</td>
<td>43.64 (28.66)</td>
</tr>
<tr>
<td>SDW × DMC</td>
<td>97.81 (27.77)**</td>
<td>97.81 (27.77)**</td>
<td>97.81 (27.77)**</td>
</tr>
<tr>
<td>R-square (adjusted)</td>
<td>0.10</td>
<td>0.14†</td>
<td>0.24**</td>
</tr>
<tr>
<td>R-square change</td>
<td>0.04†</td>
<td>0.10**</td>
<td></td>
</tr>
</tbody>
</table>

Note: SC = Supply Chain. N = 71 Cross-functional Teams. Unstandardized regression coefficients are shown; standard errors are noted within parentheses.
*p < 0.05.
**p < 0.01.

FIGURE 2  Study 1 – Number of SC disruption warnings, decision-making centralization, and firm robustness

STUDY 2

Sample and procedure

As in Study 1, we were unable to obtain a representative sample from the entire population of SC professionals for Study 2 and therefore collected data from a smaller (convenience) subpopulation. This subpopulation comprises students participating in a postgraduate course in strategic SC management at a university in the Netherlands. This subpopulation incorporated the full SC management master’s program cohort of the respective university, as well as students from other business-related master’s programs that chose the course as an elective. Of the participants, 87% were SC management students, while 76% were Dutch nationals. We focused on this specific subpopulation because the SC course participants were close to finishing their master’s degree and had solid knowledge of SC management. All members of the subpopulation were invited and participated in our research (i.e., the response rate was 100%), thereby avoiding the potential for non-response bias.

As part of the postgraduate course in strategic SC management, we formed four-person student teams and collected data on how these teams performed in a total of 138 simulation rounds of TFC (i.e., 23 teams, each participating in six simulation rounds). We composed the cross-functional teams to ensure between-team similarity in members’ backgrounds and study programs. On average, 28.26% of the individuals in teams were female (SD = 29.95). Within teams, students could choose their own roles, which enabled them to assume roles that aligned best with their expertise. Moreover, students were co-located and could freely communicate with one another. Teams received training before their first simulation round, which included reading material, an illustrated presentation, and a group
session in which decisions for each role were explained. Students then participated in six computer-based simulations during which they could encounter varying numbers of SC disruption warnings. Teams had, on average, one week to complete each simulation round and completed the whole simulation in six weeks. We aimed to galvanize students by awarding bonus grade points to high-performing teams, as well as by setting assignments related to the simulation, team performance, and SC understanding.

After the completion of each simulation round, we asked all participants to complete a survey containing items on internal integration problems and decision-making centralization. Having established that aggregation was statistically justified by assessing interrater reliability, we combined participants’ ratings to form team-level variables. We then combined all objective and survey data to create a pooled cross-sectional time-series dataset, comprising complete information on our independent, moderating, and mediating variables over a total of 138 simulation rounds.

**Measures**

**Number of SC disruption warnings**

We counted the total number of internal and external SC disruption warnings a team had to handle during a TFC simulation round. This variable ranged from zero (i.e., the team had no SC disruption warnings to deal with during that round) to four (i.e., the team had to deal with four potential problems during that round). Internal SC disruption warnings originated from inside the firm and referred to a possible strike in the inbound or outbound warehouse. Warnings for internal risks were sent to teams where the workload in either warehouse was too high. External SC disruption warnings originated from outside the firm and included possible delays in the supply of raw materials due to pirate attacks or hurricanes. As in Study 1, SC disruptions and their warnings were consistently timed and sequenced across all teams: warehouse strikes occurred in rounds 4, 5, and 6; pirate attacks in rounds 5 and 6; and a hurricane in round 4. The corresponding warning for each of these SC disruptions was consistently available to teams during decision-making at the beginning of the corresponding round.

**Internal integration problems**

Within firms using a cross-functional team to manage SC disruption warnings, firm-level internal integration should be achieved through alignment between the managers who are part of the team. Current measures in SC literature are not designed to specifically capture such internal integration (cf. Flynn et al., 2010; Schoenherr & Swink, 2012). Therefore, we employed an established measure from team research to gauge the degree to which the efforts of members of a firm’s cross-functional team were appropriately integrated and coordinated. Specifically, we used the coordination scale developed by Lewis (2003) and measured internal integration problems by gauging the degree to which members experienced integration problems in their team. We selected three high-loading items from this scale to keep the survey short and to prevent survey fatigue (as respondents had to complete the survey six times; Hinkin, 1995). Participants expressed their agreement with three reverse-scored items: “We worked in a well-coordinated fashion”; “We had few misunderstandings about what to do”; and “We accomplished the task smoothly and efficiently.” Responses were given on a 5-point Likert scale (1 = completely disagree; 5 = completely agree). Cronbach’s alpha ranged from 0.68 to 0.78 across the six rounds.

To test the consistency of team members’ ratings of internal integration problems, we followed recommendations by Boyer and Verma (2000) by first calculating the intraclass correlation coefficient 1 (ICC[1]). This statistic estimates the proportion of a measure’s total variance explained by group membership. In our sample, the ICC(1) ranged from 0.06 to 0.39. Then, we calculated the ICC(2) statistic, which indicates whether (a) participants rated the internal integration problems within their own team consistently and (b) scores differed between members of different teams. ICC(2) ranged from 0.20 to 0.73. Except for round 1, the ICC(1) and ICC(2) values fell within the acceptable range for all rounds (Woehr et al., 2015). Therefore, we carried out all analyses for Study 2 twice, with round 1 data included and excluded, respectively. As our results remained largely unchanged when excluding round 1 data, we chose to include these data in the analyses.

**Decision-making centralization**

We used the same centralization measure as in Study 1 and collected data on centralization after each and every round.

**Firm robustness**

As in Study 1, we operationalized robustness as the degree to which a cross-functional team avoided a decline in its firm’s ROI between rounds while facing potential SC disruptions. As explained in Appendix S3, we controlled for prior round ROI by including a random first-order autoregressive coefficient.
Control variables

As in Study 1, we controlled for decision-making density. We also controlled for the heterogeneity in SC disruption warnings faced by different teams, as some teams encountered more internal versus external disruptions than other teams throughout the simulation. Compared with internal disruptions, external SC disruptions had more far-reaching consequences (delaying the supply of raw materials for extended periods). To account for this heterogeneity, we added the variable “SC disruption warning content” as a team-level covariate in our analyses. We calculated it by dividing the number of internal disruption warnings by the total number of disruptions that the team faced during the simulation.

Data analysis

Following the above procedures, we obtained multilevel data on 138 simulation rounds (level 1—measurement occasions) nested within 23 cross-functional teams (level 2—teams). This nested data structure violates the assumption of the non-independence of observations in OLS and MANOVA (Snijders & Bosker, 1999). Therefore, we used a multilevel modeling (MLM) time-series approach and ran regression models with random intercepts and random first-order autoregressive (AR1) slopes to test our hypotheses. Such techniques explicitly model the statistical dependence in the data and, therefore, provide reliable estimates (Heck & Thomas, 2015). The random intercepts in these models capture teams’ baseline values on the outcome variables and thus control for variance due to the nesting of observations within teams (Krone et al., 2016; Zhang et al., 2018). The random AR1 coefficients capture the degree to which values obtained at measurement time \( t – 1 \) carry over into the values obtained at time \( t \). As such, they allow us to partial out the variance caused by serial correlations between measurements. Furthermore, to prevent our level-1 parameters from being biased by parallel level-2 relationships, we ran so-called “unconflated” multilevel models (Krull & MacKinnon, 2001; Preacher et al., 2011; Zhang et al., 2009). In these models, all level-1 predictor variables are group-mean centered, and the level-2 mean values of the predictors are used to predict the level-2 values of the outcome variable. Group-mean centering removes between-team differences in variables and ensures that level-1 predictors are uncorrelated with level-2 predictors (Aguinis et al., 2013). Controlling for predictors’ group-mean values removes any variance in the outcome variables due to level-2 effects, resulting in unbiased parameters.

Using this approach, we first ran separate analyses to test H1–H3. Next, we followed the causal-step procedure recommended by Rungtusanatham et al. (2014) for assessing mediation in SC research, as adjusted by Hayes (2017) for testing the proposed mediated moderation effect (H4). Specifically, we examined whether each of the following requirements was met: (a) the interaction between the number of SC disruption warnings, decision-making centralization, and firm robustness is statistically different from zero (i.e., H1); (b) the interaction between the number of SC disruption warnings, decision-making centralization, and internal integration problems is statistically different from zero (i.e., H2); (c) the direct relationship between internal integration problems and firm robustness is statistically different from zero (i.e., H3); and (d) the interaction term of the number of SC disruption warnings and decision-making centralization becomes non-significant when the mediator is added to the equation for firm robustness.

To further examine the pattern of relationships suggested by H4, we calculated the conditional indirect relationships between the number of SC disruption warnings and firm robustness (Hayes, 2017). We followed the procedure outlined by Edwards and Lambert (2007) by first calculating the simple slopes between the predictor and mediator at high (+1 SD) and low (−1 SD) levels of the moderator. Second, we multiplied the simple slopes with the coefficient of the relationship between the mediator and outcome to obtain the conditional indirect effect at high (+1 SD) and low (−1 SD) levels of the moderator. Next, we assessed the 95% confidence intervals to determine the significance of the indirect effect. If the confidence interval excludes 0, the indirect effect is statistically significant (Hayes, 2017). These confidence intervals were computed using Bayesian estimation because conditional indirect effects are always skewed, and their confidence intervals cannot be reliably estimated with statistical techniques that assume normally distributed parameters (Edwards & Lambert, 2007). Bayesian analyses do not expect or require normally distributed data and, hence, are recommended for assessing mediated relationships (Rungtusanatham et al., 2014).

Results

Descriptive statistics

Means, standard deviations, and correlations for the Study 2 variables are presented in Table 3. Because these correlations do not account for our nested data structure, they should be interpreted with caution. As in Study 1, firm robustness was not observed directly but modeled in the MLM time-series analyses as the change in firm performance between rounds.

Hypotheses tests

Consistent with H1, we found a significant interactive relationship between the number of SC disruption
warnings, decision-making centralization, and firm robustness ($B = 40.97, SE = 19.19, p < 0.05$; see Table 5, Model 4). Simple slopes analyses indicated a non-significant relationship between the number of SC disruption warnings and changes in firm ROI when decision-making centralization was high (see Figure 3; relationship at $+1 SD = 1.53$, 95% confidence interval = $-3.73$ to $6.60$) but a significant negative relationship between them when decision-making centralization was low (relationship at $-1 SD = -6.66$, 95% confidence interval = $-10.12$ to $-3.21$). These results indicate that cross-functional teams with a centralized decision-making structure were able to preserve their firms’ ROI levels (i.e., higher robustness) when confronted with larger numbers of SC disruption warnings, whereas teams with less centralized decision-making suffered a decline in their firms’ ROI (i.e., lower robustness).

In line with H2, we found a significant interactive relationship between the number of SC disruption warnings, decision-making centralization, and internal integration problems when decision-making centralization was low (relationship at $-1 SD = 0.17$, 95% confidence interval = $0.05$ to $0.28$) but a non-significant relationship between them when decision-making centralization was high (relationship at $+1 SD = -0.13$, 95% confidence interval = $-0.30$ to $0.04$).

In line with H3, we found a statistically significant negative relationship between internal integration problems and firm robustness ($B = -10.69, SE = 2.92, p < 0.01$; see Table 5, Model 5). Moreover, the interactive relation between the number of SC disruption warnings, decision-making centralization, and firm robustness became non-significant after adding the internal integration problems variable to the model ($B = 25.79, SE = 18.91, n.s.$; see Table 5, Model 5). Together with the findings supporting H2 and H3, this suggests that the interactive relationship between the number of SC disruption warnings, decision-making centralization, and firm robustness is fully mediated by internal integration problems, which supports H4 (Hayes, 2017). Follow-up analyses revealed that the mediated negative indirect relationship between the number of SC disruption warnings and firm robustness was significant when decision-making centralization

### Table 3: Study 2 – Descriptive statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>$M$</th>
<th>$SD$</th>
<th>$r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Decision-making density</td>
<td>0.75</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td>2 Decision-making centralization</td>
<td>0.19</td>
<td>0.10</td>
<td>$-0.74^{**}$</td>
</tr>
<tr>
<td>3 Number of SC disruption warnings</td>
<td>0.51</td>
<td>1.05</td>
<td>0.03</td>
</tr>
<tr>
<td>4 Internal integration problems</td>
<td>4.28</td>
<td>0.50</td>
<td>$-0.33^{**}$</td>
</tr>
<tr>
<td>5 ROI at simulation round</td>
<td>$-10.14$</td>
<td>14.42</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Note: SC = Supply Chain. $N = 138$ Simulation Rounds.

* $p < 0.05$.

** $p < 0.01$.

![Figure 3](image-url)
was low (indirect relationship at −1 SD = −1.31, 95% confidence interval = −2.90 to −0.29) but non-significant when decision-making centralization was high (indirect relationship at +1 SD = 0.89, 95% confidence interval = −0.60 to 2.83). Appendix S4 details the outcomes of the statistical robustness checks for Study 2.

**DISCUSSION AND CONCLUSION**

**Theoretical contributions**

The ability to use SC disruption warnings in preparation for SC disruptions has been highlighted as an important aspect...
of risk management (Craighead et al., 2007), yet knowledge of how firms can effectively and efficiently derive response strategies remains very limited (Bode & Macdonald, 2017; Timmer & Kaufmann, 2019). Although SC theory suggests that a cross-functional team can help in dealing with risks, and ensuring that potential SC problems are addressed in an integrative manner, empirical studies are lacking. The field of team research suggests, however, that cross-functional teams differ widely in their ability to deal with risks (e.g., Ellis, 2006; Salas et al., 2000; Uitdewilligen & Waller, 2018). This study, therefore, empirically examined when and how some cross-functional teams are better able than others to handle (multiple) SC disruption warnings, drawing from OIPT and GIPT.

Scholars have previously proposed that SC disruption warnings may enable firms to take precautionary measures to avoid disruptions impacting organizational performance (Craighead et al., 2007) and that firms with effective leadership may be successful in doing so (Durach et al., 2015). However, to the best of our knowledge, empirical support for these propositions has not been provided. Our study empirically shows and details the decision-making structure and solutions that may promote effective responses to varying numbers of SC disruption warnings. Specifically, we provide additional detail on how a cross-functional team can best process information when faced with different amounts of information-processing demands. We show that a cross-functional team can more effectively ensure firm robustness by using more centralized decision-making to handle many simultaneous SC disruption warnings. We also identified prevention of internal integration problems as an important mediating mechanism through which decision-making centralization in the cross-functional team may translate into

<table>
<thead>
<tr>
<th>TABLE 5 Study 2 – Multilevel estimates for firm robustness</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Firm robustness</strong></td>
</tr>
<tr>
<td>Model 1 (Null)</td>
</tr>
<tr>
<td><strong>Level 1 (L1)</strong></td>
</tr>
<tr>
<td>Intercept (γ_{00})</td>
</tr>
<tr>
<td>Autoregressive coefficient (γ_{10})</td>
</tr>
<tr>
<td>SC disruption warnings (SDW) (γ_{30})</td>
</tr>
<tr>
<td>Decision-making centralization (DMC) (γ_{40})</td>
</tr>
<tr>
<td>SDW × DMC (γ_{50})</td>
</tr>
<tr>
<td>Internal integration problems (γ_{60})</td>
</tr>
<tr>
<td><strong>Level 2 (L2)</strong></td>
</tr>
<tr>
<td>Mean decision-making density (γ_{01})</td>
</tr>
<tr>
<td>SC disruption warning content (γ_{02})</td>
</tr>
<tr>
<td>Mean SC disruption warnings (γ_{03})</td>
</tr>
<tr>
<td>Mean decision-making centralization (γ_{04})</td>
</tr>
<tr>
<td>Internal integration problems (γ_{05})</td>
</tr>
<tr>
<td><strong>Variance components</strong></td>
</tr>
<tr>
<td>Within-team (L1) variance (σ2)</td>
</tr>
<tr>
<td>Intercept (L2) variance (τ00)</td>
</tr>
<tr>
<td>Slope (L2) variance (τ11)</td>
</tr>
<tr>
<td>Slope-intercept covariance (τ01)</td>
</tr>
<tr>
<td><strong>Additional information</strong></td>
</tr>
<tr>
<td>Bayesian Deviance Information Criterion (L1)</td>
</tr>
<tr>
<td>Estimated Number of Parameters (pD)</td>
</tr>
<tr>
<td>Pseudo R-square (L1)</td>
</tr>
</tbody>
</table>

**Note:** N = 138 simulation rounds. Unstandardized regression coefficients are shown; standard errors are noted within parentheses. SC = Supply Chain.

*p < 0.05.

**p < 0.01.

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Craighead et al., 2007; Bode & Macdonald, 2017; Timmer & Kaufmann, 2019.
firm robustness. We found that when there was orchestrated decision-making within the cross-functional team, internal integration problems were more likely to be prevented than in teams with less centralized decision-making. These findings contribute to existing research on the relationship between internal and external SC integration (Leuschner et al., 2013; Schoenherr & Swink, 2012), providing new knowledge on the process leading to internal integration within a cross-functional team tasked with managing external SC relations.

Furthermore, our study contributes to the literature on SC risk management. Rather than focusing on how firms can recover following SC disruptions, we explored how firms can prevent SC disruptions from impacting their performance in the first place. We examined how a cross-functional team may ensure firm robustness by effectively heeding SC disruption warnings and handling their information-processing demands. By integrating OIPT with insights from team research, we demonstrated the importance of considering both the micro-level decision-making structure within the cross-functional team and the macro-level environmental conditions facing the firm (i.e., the number of SC disruption warnings) when examining firm robustness. As such, this study answers scholars’ call for more behavioral SC research to “provide the mechanisms through which to bridge [micro and strategic] levels of analysis” (Bendoly & Bachrach, 2015, p. 401). Furthermore, this study validates the pivotal role of the cross-functional team in not only reactive SC risk management strategies, as Blackhurst et al. (2011) suggested, but also proactive strategies to create robustness.

Our study also contributes to research on behavioral operations management by providing a fresh perspective on team processes. According to Bendoly et al. (2010, p. 449), “much of the existing research has focused on how a failure to include behavioral influences can lead to operational systems which fail.” This perspective explains why normative (mathematical) models, decision rules, and other tools and designs for operations and SC management do not perform as expected when implemented in practice. As such, much of the contemporary literature on behavioral operations management aims to use behavioral theories to overcome such failures. We add to this research area by showing how adapting a team’s decision-making structure to the environment’s information-processing requirements may prevent internal integration problems and, in turn, improve firm robustness. Thus, our findings underscore the importance of considering human behavior as the micro-level foundation of effective firm-level responses to potential SC problems (Fahimnia et al., 2019; Timmer & Kaufmann, 2019); more specifically, they answer the call for research “that strives to trace the cause–effect paths of SC phenomena to the lowest level from which they emerge” (Schorsch et al., 2017, p. 255).

These contributions to SC research may also be valuable in other domains, such as research focused on team effectiveness. Like SC scholars, team researchers have primarily focused on how teams handle disruptions that have already materialized, overlooking that most teams encounter warnings that may enable them to prevent adverse events affecting firm performance. Moreover, prior research on teams has adopted an intra-team focus, exploring how within-team processes (Maynard et al., 2015) and team-level performance can be restored following internal disruptions (Bunderson et al., 2014; LePine, 2005; Summers et al., 2012). This study complements existing team research by considering that many disruptions originate outside the team and have consequences that reach beyond it and have effects on performance that can be proactively avoided by responding to warnings. Therefore, our study answers calls within the team research domain for more realistic perspectives on how cross-functional teams handle unforeseen situations and disruptions (Maynard et al., 2015).

Theoretically, we contribute to OIPT and GIPT. OIPT identifies the cross-functional team as an effective solution for firms dealing with increased information-processing demands due to several SC disruption warnings. However, OIPT is a macro-level theory that does not consider the micro-level processes that may ultimately determine if and how a cross-functional team may realize its potential for dealing with SC disruption warnings. We help to address this issue by illustrating how OIPT can be extended with insights from GIPT to examine the micro-foundations determining if and how a cross-functional team may increase an organization’s robustness. Specifically, we examined how centralization in a team’s decision-making processes may help to realize its potential to ensure firm robustness. In doing so, we also further contribute to GIPT. Prior applications of GIPT have illustrated the benefits of centralized decision-making for team information-processing capacities (Davison et al., 2012; Lanaj et al., 2013; Mell et al., 2014) but have not clarified when and why such capacities are needed. We help to address this issue by illustrating how GIPT can be extended with OIPT to identify contextual moderators and conceptual mechanisms that may influence the importance of centralized team decision-making processes. Specifically, we showed that centralized team decision-making is particularly important when teams face high information-processing demands through multiple disruption warnings in their SC.

Managerial contributions

Our findings may help to guide firms in effectively using a cross-functional team to respond to SC disruption warnings and ensure firm robustness. Pending further validation of our results, we recommend that cross-functional teams should use more centralized decision-making in situations
characterized by several SC disruption warnings. Without one or two central team members to organize information flows and orchestrate subsequent decision-making, a cross-functional team can be easily overwhelmed by the information-processing demands associated with many SC disruption warnings. To ensure that the cross-functional team can rely on central members with the capacity and motivation to guide decision-making, organizational leaders may draw from literature on emergent leadership (e.g., de Souza & Klein, 1995; Taggar et al., 1999) and assign members with high commitment to assigned goals, high individual task ability, and appropriate personality characteristics such as emotional stability and extraversion. Finally, our findings show that reduced robustness may emerge through increased internal integration problems within the cross-functional team. By closely monitoring the internal integration processes within the team, organizational leaders may thus be able to identify early warnings of potential declining robustness and take appropriate action.

Limitations and future research

Some limitations should be considered when interpreting our findings. First, we were unable to sample the entire population of professionals working in SC management and, therefore, collected data from convenience subpopulations in Study 1 (professionals in the global SC management challenge) and Study 2 (students pursuing a postgraduate strategic SC management course). This sampling approach may limit the generalizability of our findings. Also, our use of student participants in Study 2 could limit our findings’ generalizability to actual firms. Such concerns may be somewhat alleviated by the diverse composition of the professional sample in Study 1, Study 2’s examination of postgraduate students with SC knowledge, and our two-study design in which results from Study 1 were compared with those from Study 2 (Scandura & Williams, 2000). However, to fully understand the extent to which our findings generalize, replication studies are needed that use probability (e.g., stratified or random) sampling procedures to draw representative samples from the entire population of professionals working in SC management. Considering that the teams in our professional sample (Study 1) comprised members with relatively diverse career paths, mostly non-managerial backgrounds, and an average of ten years’ experience, it is particularly important to test our predictions using samples of professionals with extensive experience (i.e., 20 years or more), homogeneous (i.e., specialist) career paths, and managerial backgrounds.

Second, we could only collect longitudinal data on a modest number of teams in Study 2, which may have decreased the statistical power of our analyses. We attempted to reduce this concern as much as possible by collecting multiple observations per team and using a two-study research design in which we cross-validated part of Study 2’s findings in a larger sample. Moreover, the sample size in Study 2 is comparable to that used in other research collecting multiple waves of data from teams (Uy et al., 2010) and even compares favorably to SC research using simulation or experimental research designs in group settings (e.g., the Beer game; Croson & Donohue, 2006). Nevertheless, it is important to test our predictions in larger samples, comprising 100 or more observations of teams dealing with SC disruption warnings, to increase confidence in our findings. To overcome the challenges associated with recruiting large samples, we recommend using intensive longitudinal or experience-sampling research designs that enable researchers to collect, combine, and analyze multiple observations from multiple teams (Uy et al., 2010). Alternatively, researchers can rely on meta-analytical research designs in which accumulated evidence from multiple smaller samples can be reliably integrated and assessed (e.g., Manhart et al., 2020).

Third, we were limited in the number of control variables we could consider in our research, and could not experimentally control or manipulate all relevant independent variables. Consequently, omitted variables may have biased our results to the extent they were correlated with our independent variable and determinants of our dependent variable (Ketokivi & McIntosh, 2017). Although our longitudinal, multi-source research design and exogenous independent variable may somewhat alleviate this concern, we fully acknowledge the importance of future research to check the robustness of our findings. True laboratory experiments in which all predictor variables are experimentally manipulated may prove useful in this regard. Alternatively, future research could measure and statistically control for important variables that we omitted, such as team members’ perceived ownership of firm-wide production processes (Parker & Axtell, 2001) or organizational identification (de Vries et al., 2014): these essential motivational constructs may determine whether team members will proactively deal with SC disruptions to ensure firm robustness. Additionally, prior experience with disruption warnings might also be a relevant covariate for consideration in further research.

Fourth, the relatively small effect sizes reported in our studies may raise concerns regarding the practical significance of our findings. The effect sizes used to assess our hypotheses meet the criteria for classification as “medium” based on empirically derived benchmarks (i.e., medium effect sizes range between 0.10 and 0.26; Bosco et al., 2015). However, additional research is needed to further assess our findings’ practical significance. Future research could, for example, use the binomial effect size display method to evaluate and demonstrate the extent to which our findings translate into actual firm robustness (e.g., de Vries et al., 2016).
A fifth and more general limitation of multi-round simulation studies is that their results can be affected by participants’ endgame strategies. Such endgame strategies may cause participants to engage in opportunistic behavior in the final round of simulations to maximize short-term profits (Bruttel et al., 2012). To assess this, we examined whether the teams in Study 1 and Study 2 had reduced their long-term investments to maximize short-term profits in the final round of the simulation. The results reveal a steady increase in investments over the course of the simulations in both studies, rather than a decline in the final round. This indicates that teams did not use opportunistic endgame strategies to maximize short-term profits. More specifically, teams in Study 1 invested €5.24 M on average in the final round, compared to an average of €4.63 M in the preceding rounds; teams in Study 2 invested €4.28 M on average in the final round, compared with an average of €4.06 M in the preceding rounds.

Sixth, to ensure comparability between the teams in our research, we exposed them to a limited set of SC disruption warnings that varied little in content or possible effects. We suspect that, in reality, disruption warnings may be more heterogeneous. They may, for example, refer to disruptions that have short-term effects or could affect the firm’s functioning after several months or even years. Furthermore, SC disruption warnings may present themselves gradually, through a sequence of small discrepancies that may easily go unnoticed, or they may be more salient and emerge abruptly. We encourage scholars to extend our research by pursuing more detailed insights into how firms may effectively manage different SC disruption warnings.

Finally, we kept team size consistently small in our studies. In reality, however, teams may vary in size and contain significantly more than four members. Such variance in team size may have important implications for our predictions. Specifically, we speculate that decision-making centralization may become even more important in larger teams, as information about SC disruption warnings must be shared and discussed with a greater number of fellow team members. As such, larger teams may become more easily overloaded when facing more SC disruption warnings, which may increase the importance of centralized decision-making. Examining our predictions in samples of teams that are larger and vary in size (e.g., comprising 3–20 team members) may, therefore, be an important future research direction. Such research could include team size as a moderator in the relationship between centralized decision-making and robustness to determine whether the importance of centralized decision-making hinges on the number of team members.

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REFERENCES


**AUTHOR BIOGRAPHIES**

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section.

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