Convergence of Collaborative Behavior in Virtual Teams: The Role of External Crises and Implications for Performance

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Abstract:

Organizations have increasingly used virtual teams (VTs) in recent years (e.g., Hertel et al., 2005; Martins et al., 2004; Taras et al., 2019). This trend has been accelerated by the recent COVID-19 pandemic and corresponding work from home mandates (Klonek et al., 2022). VTs are groups of spatially dispersed individuals who work together to reach a common objective by relying on telecommunication and information technologies (Martins et al., 2004). To accomplish tasks, team members interact in collaborative behavioral processes (Rousseau et al., 2006). As team members influence each other during teamwork (Bedwell et al., 2012), this interaction can lead to a shared behavioral climate and the emergence of interindividual consensus (or the opposite: dissent; Fulmer & Ostroff, 2016). According to Lang et al. (2018), we define the emergence of consensus as the increasing similarity among a shared within-unit phenomenon among VT members over time (i.e., the convergence of shared within-unit phenomenon). Therefore, collaborative behavior consensus is a process of intrateam behavioral convergence that emerges over time from a lower level (e.g., individual) to a higher level (e.g., team). Consensus is particularly important for (virtual) teams because it is associated with less conflict and stronger intrateam relationships (González-Romá & Hernández, 2014) and can affect team outcomes (Bedwell et al., 2012; Fulmer & Ostroff, 2016).

Keywords: virtual teams | collaborative behavior consensus | external crisis | team performance | multilevel group-process framework

Article:

In addition to the geographic dispersion of team members (e.g., Martins et al., 2004; Taras et al., 2019), intrateam processes can be impaired by external factors such as environmental crises (Majchrzak et al., 2007). The COVID-19 pandemic is both an example and a specific case of an external environmental crisis that significantly impacted the work context of many employees (Caligiuri et al., 2020). Governments worldwide introduced various measures (e.g., mask mandates and social distancing rules) to address the varying effects of the pandemic, which affected the work habits of many employees (Feitosa & Salas, 2021). As VTs already face significant challenges (e.g., lack of physical contact, conflict, feelings of isolation, and trust) to teamwork (Hertel et al., 2005), collaborating in VTs during the pandemic has presented additional challenges for many individuals (Klonek et al., 2022).

Previous studies have examined the influence of external events on individuals, teams, and organizations (e.g., Reivich & Shatté, 2002). Additionally, literature focused on aspects related to the shift to virtual work due to the pandemic (e.g., Bennett et al., 2021; Chong et al., 2020). However, still little is known about the impacts of global uncertainty and volatile environmental situations (e.g., pandemic-related factors) on individuals and their behaviors in VTs (Caligiuri et al., 2020). Furthermore, research is scarce regarding the mechanisms and consequences of (collaborative) behavior consensus and, thus, regarding whether consensus can emerge in certain forms of behavior in VTs and how it affects outcomes (Fulmer & Ostroff, 2016). Inferring from the open systems theory (Katz & Kahn, 1978), in conjunction with a phenomenon-driven approach (Hambrick, 2007) and using the multilevel group-process framework (MGPF; Lang et al., 2019), we examine the emergence of collaborative behavioral consensus under the impact of COVID-19 and the implications of consensus emergence on VTs' performance.

Our study contributes to the literature on VTs in four ways. First, we extend the understudied topic of consensus emergence in behavior (Fulmer & Ostroff, 2016). Previous research studies have mainly focused on the emergence (i.e., consensus) of cognition (e.g., Loh et al., 2021; Randall et al., 2011), affections (e.g., Madden et al., 2012), or emotions (e.g., Uy et al., 2021). We increase our understanding of emergent phenomena in the context of the open systems theory (Katz & Kahn, 1978) by focusing on the emergence of consensus in collaborative behavior in VTs.

Second, multilevel research primarily considers emergent constructs to be static (Kozlowski, 2015) and assumes that a higher level phenomenon results from emergence processes at a lower level (Kozlowski & Chao, 2012). We went beyond this view and examined the emergence of collaborative behavior consensus as a dynamic multilevel process (Cronin et al., 2011). Therefore, we contribute to emergence research by considering and empirically testing the interplay between different levels. In doing so, we combined key recommendations from the literature on consensus emergence research by moving beyond cross-sectional research designs. We employed a multilevel data structure (i.e., time, individual, and team levels) and applied more advanced statistical techniques (i.e., the MGPF; Lang et al., 2019) to model the process of emergence and thus consensus directly over time (B. S. Bell & Kozlowski, 2012; Kozlowski, 2015).

Third, we contribute to the literature on the determinants of consensus emergence (e.g., DeRue et al., 2010; Fulmer & Ostroff, 2016) in collaborative behavior in VTs during an external crisis (Caligiuri et al., 2020). Based on a phenomenon-driven approach (Hambrick, 2007), we used the specific case of the COVID-19 pandemic to identify, disentangle, and empirically test factors (related to VT members) aroused outside of the workplace that affect the emergence of consensus in collaborative behavior in VTs. We explore a relatively understudied aspect concerning external forces in the context of consensus tendencies (Cronin et al., 2011; Humphrey & Aime, 2014) when VT members are confronted with major environmental adversity (e.g., Garro-Abarca et al., 2021). In doing so, our approach leads to new insights (Hambrick, 2007) on how the open systems theory (Katz & Kahn, 1978) can be extended to behavioral consensus in VTs collaborating under the influence of an external crisis (i.e., the COVID-19 pandemic).

Fourth, our study contributes to the literature on VT outcomes (e.g., Mell et al., 2021; Taras et al., 2019) by examining the relationship between collaborative behavior consensus and performance in VTs. Although previous studies have examined whether shared team phenomena directly (e.g., team passion; Uy et al., 2021) or indirectly (team climate; González-Romá & Hernández, 2014) affect team outcomes, evidence of the effect of emergent behavioral phenomena (e.g., collaborative behavior consensus) on performance within VTs is still lacking. Therefore, our study enhances the open systems theory (Katz & Kahn, 1978) in terms of understanding the consequences of emergent phenomena (i.e., collaborative behavior consensus) on VT outcomes.

Theoretical Background and Hypotheses Development

Collaborative Behavior in the Context of Virtual Teams

Collaborative behavior is a form of teamwork behavior that focuses on task accomplishment. It mainly occurs in the execution of teamwork, where team members implement planned activities (Rousseau et al., 2006). This process aims to transform team input (e.g., team member characteristics or skills) into team output (e.g., performance; Marks et al., 2001). Drawing on the integrated framework of Rousseau et al. (2006), we distinguish collaborative behavior in teams in three dimensions: coordination, communication, and cooperation. Coordination is a behavioral process that ensures the integration and completion of team members' activities to accomplish an assigned task under time constraints. It is based on intrateam interactions and can be affected by internal and external phenomena (Fisher, 2014; Marks et al., 2001). Communication (i.e., information sharing) is based on the exchange of task-related information among the team members, including the level of communication. A high level of communication increases the team's effectiveness by ensuring the availability of information and its dissemination among team members (e.g., Marks et al., 2001; Salas et al., 2005). Last, cooperation is the willingness to contribute to accomplishing team goals, expressed in the individual effort of team members in completing tasks. Cooperative behavior involves team members working together to achieve the goals that an individual could not achieve alone (Wagner, 1995).

The collaborative environments in VTs differ systematically from those in face-to-face teams (Gilson et al., 2015; Martins et al., 2004). VTs face a lack of physical contact and often have to deal with time zone differences due to the geographic dispersion of team members (Hertel et al., 2005). VTs are often structured to work on a specific task, and team members may not know each other prior to working together (Jarvenpaa & Leidner, 1999). Processes within VTs focus on task accomplishment, as the task is the primary focus of VT collaboration (Maynard & Gilson, 2014). In this way, VTs exhibit behavior that is task-oriented (Cramton, 2001). Despite the fact that VTs face multiple challenges related to cooperation or communication (Mesmer-Magnus & Dechurch, 2009; Ortiz de Guinea et al., 2012), VT members direct their collaborative behaviors to the virtual environment (Ahuja & Galvin, 2003). In doing so, team members first focus on establishing behavioral tactics for task completion before establishing other processes (Mathieu et al., 2009; Maynard & Gilson, 2014). Thus, during collaboration, team members place the collaborative behavioral component of teamwork at the center of their attention.

The Emergence of Collaborative Behavior Consensus in Virtual Teams

Collaborative behavior is a dynamic interindividual process that develops over the course of teamwork and can change over time (Bedwell et al., 2012; Chan, 1998). At the beginning of a team project, team members may differ significantly in their collaborative behavior owing to differences in knowledge, perceptions, or beliefs (Tasa et al., 2007). As they collaborate, team members develop effective behavioral strategies that direct, focus, and stimulate individual efforts to facilitate task completion. Team members align their efforts with the collective efforts of the (virtual) team to achieve a common goal. In this way, interactions among team members may result in similar behavioral reactions and thus create a shared climate (Chan, 1998; Kozlowski & Klein, 2000). While McGrath (1991) describes this phenomenon as the synchronization of individuals' processes (e.g., behavior), Kozlowski and Klein (2000) add that individual behavioral processes can lead to a collective phenomenon referred to as the emergence of consensus in behavior. It represents a team-level "outcome" of the VT members' shared collective behavior (Kozlowski & Klein, 2000).

To theoretically explain the mechanisms of consensus emergence over time, we draw from the open systems theory (Katz & Kahn, 1978). The theory can be used to explain human behavior as a multilevel phenomenon in organizations and groups. According to the open systems theory, there are different levels of systems in organizations that are interrelated. Individuals are involved in interaction and exchange processes while working. As a consequence, their behavior can manifest as a higher level output resulting from a reciprocal action at a lower level. Thus, this output reflects the emergence of behavioral patterns (i.e., behavioral consensus) that goes beyond the mere aggregation of individual actions. In this way, "patterned" human behavior (i.e., the emergence of behavioral consensus) can be seen as the essence of organizations (Katz & Kahn, 1978). Applying open systems theory to the team environment, emergence is a process in which the interactions of team members (i.e., individual-level units) are revealed in a new team phenomenon (i.e., at the team level; Kozlowski & Chao, 2012). As the collaboration progresses, team members are exposed to a series of event cycles that require action and reaction. Due to social influences (e.g., maintenance of social connections) or psychological mechanisms (e.g., an increase of self-identification), team members may develop overlapping views that lead to behavioral adaptation and, thus, to a behavioral similarity in responding to specific circumstances. The emergent phenomenon of behavior is multilevel and time-dependent by nature, as lower level interactions are required to develop team-level events. The result of these emergence processes can be convergence in the shared within-unit phenomenon and, thus, the emergence of consensus (i.e., lower variance at a higher level due to behavioral similarity; Morgeson & Hofmann, 1999). We argue that VT members converge in collaborative behavior over time and thus develop a behavioral consensus. Although virtual working environments may challenge collaboration (Hertel et al., 2005; Mesmer-Magnus & Dechurch, 2009; Ortiz de Guinea et al., 2012), VTs primarily focus on task completion. In this way, VTs behave collaboratively (i.e., team-oriented), as this is considered an important component of task completion (Kozlowski et al., 1999) in VTs. Consequently, VT members develop a shared view of their work and align their collaborative behavior, leading to a shared behavioral orientation on how to collaborate to complete the assigned task (i.e., collaborative behavior consensus; Maynard & Gilson, 2014; Weick, 1995). Therefore, we hypothesize the following:

Hypothesis 1: VT members converge in their collaborative behavior over time, leading to the emergence of collaborative behavior consensus in VTs.

The COVID-19 Pandemic and the Emergence of Consensus in Collaborative Behavior in Virtual Teams

Consensus is a process that emerges over time. According to the open systems theory (Katz & Kahn, 1978), contextual facets (i.e., events) related to team members can affect the consensus emergence process (Kozlowski & Chao, 2012). While some may weaken or hinder consensus, others accelerate or enhance it (Kozlowski, 2015; Kozlowski & Klein, 2000). Given the sudden occurrence of the COVID-19 pandemic, we used a phenomenon-driven approach (Hambrick, 2007) to expand our understanding of consensus emergence (Kozlowski & Klein, 2000) in VTs during an external crisis. The COVID-19 pandemic has featured two dynamic key facets that, while not work-specific, had an impact on the work lives of many individuals (Caligiuri et al., 2020). First, it has caused health threats (i.e., COVID-19 health threat). There were many uncertainties about the effects of contracting the virus (e.g., high mortality rates), thus making it a potential threat to health (i.e., death) for many people (Trougakos et al., 2020). Second, social distancing measures were introduced to hinder the spread of the virus (i.e., COVID-19 social distance). As both elements originate outside the workplace, they can be considered contextual moderators that are not work-specific (Caligiuri et al., 2020; Kniffin et al., 2021). However, those additional complexities affected the functioning of VTs (Klonek et al., 2022). We argue that the degree to which employees were affected by the key facets of the COVID-19 pandemic can be viewed as a contextual variable with consequences for the emergence of collaborative behavior in VTs.

COVID-19 caused dynamic health-related concerns worldwide (Williamson et al., 2020). People were either directly confronted with the health threat of the virus by losing family and friends (Marmarosh et al., 2020), by media reports, or by being indirectly affected by the quick responses of governments to decrease mortality rates. Altogether, there was a great deal of uncertainty and volatility regarding the health effects of the virus (Brammer et al., 2020). When individuals experience volatile and disruptive situations, they are required by human nature to adapt to the changing status quo, cope with unexpected problems, or develop novel solutions, which consequently requires actions that reduce other intraindividual resources (e.g., Schmeichel et al., 2003). The use of regulatory actions to manage negative experiences places further demands on the (e.g., cognitive and physical) capacities of individuals (Johns et al., 2008). Unlike constraints directly related to the immediate workplace (e.g., interindividual organizational problems; Pindek & Spector, 2016), COVID-related threats are associated with the larger environment that lies beyond personal control and can hardly be solved within the workplace. Consequently, the volatile COVID-19 (health) situation may negatively affect virtual workers (Chong et al., 2020) in VTs, as health threats result in defensive behavioral responses (van Bavel et al., 2020). Therefore, individuals tend to interact less with their team members (Gladstein & Reilly, 1985), which can affect how individuals collaborate (Powley, 2009). Therefore, we argue that the extent to which the individuals were exposed to the dynamic COVID-19 health threat affected their emergence of collaborative behavior consensus in VTs. Formative experiences such as a COVID-19 health threat can affect individuals' behavior. Individuals within the same VT can be shaped differently by a volatile situation. This leads to different interpretations of how to behave collaboratively (Caligiuri et al., 2020; Fulmer & Ostroff, 2016; Marquis & Tilcsik, 2013) and thus prevents individuals from adapting to the common behavioral orientation in their VT (i.e., negative effect on consensus emergence). In accordance with our arguments, we formulate the following hypothesis:

Hypothesis 2a: Time negatively moderates the relationship between COVID-19 health threat and collaborative behavior consensus in VTs.

The country-specific social distancing rules (e.g., lockdowns, closing of amenities, or other institutions) were another key facet of the COVID-19 pandemic that prevented the spread of the virus (i.e., COVID-19 social distancing measures). Individuals were required to avoid physical contact, resulting in decreased social exchanges (Brammer et al., 2020). Consequently, the social distancing measures directly contrasted with the basic human need for interpersonal contact (Baumeister & Leary, 1995). Thus, working in VTs during the pandemic provided ways to remain socially connected to individuals experiencing similar stressors under similar circumstances (Marmarosh et al., 2020; Rudolph et al., 2021). Unintentionally, virtual work (e.g., VTs) provided a vehicle for social interactions during the COVID-19 crisis (Caligiuri et al., 2020). In this way, the COVID-19 pandemic can make individuals aware of the (new) value of specific social ties (i.e., recalibration) and make them reinforce social interactions that they consider important in a particular situation (Jo et al., 2021). Thus, in response to the crisis measures, individuals developed certain forms of supplemental behavior that helped them interact in teams (Qin et al., 2021) and maintained interpersonal contacts. To establish or maintain social ties, individuals tend to align their interactions with those of their group. This helps with the integration into the group (Hardin & Higgins, 1996). Following this line of reasoning, we argue that COVID-19 social distance promotes individuals' interactions within their teams, which lead to the emergence of consensus (Fulmer & Ostroff, 2016; Kozlowski & Chao, 2012) in collaborative behaviors. Working with a group (i.e., VTs) provides social exchanges during volatile times (Caligiuri et al., 2020) and increases the individuals' collaborative interactions in VTs. In doing so, (virtual) team members adapt their collaborative behavior to the collaborative behavior of the group in order to participate in team activities. Individuals tend to align their efforts with the (virtual) team to become part of the group (Kozlowski & Chao, 2012) instead of remaining socially isolated due to COVID-19 social distance measures. This consensus about their interactions also inoculates VTs against the outside. On this premise, we formulate the following hypothesis:

Hypothesis 2b: Time positively moderates the relationship between COVID-19 social distance and collaborative behavior consensus in VTs.

The Role of Collaborative Behavior Consensus and Performance in Virtual Teams

The collaborative behavior of VT members has implications for the performance of VTs. However, according to literature related to the emergence of consensus (Kozlowski & Klein, 2000), the consequences of team phenomena resulting from consensus emergence should be distinguished from those resulting from aggregation (e.g., the mean level of shared phenomena; González-Romá & Hernández, 2014). Whereas aggregation accounts for the degree or extent of a shared phenomenon (e.g., level of collaborative behavior of VTs) among individuals, the emergence of consensus reflects the within-unit level of (dis)agreement in a shared phenomenon (e.g., (dis)agreement in a collaborative behavioral approach within VTs). A decreasing level of consensus (i.e., diverging variance) indicates that VT members disagree with the shared phenomenon, whereas an increasing level of consensus suggests agreement. Disagreement in a shared phenomenon can erupt in a group and lead to opposing views and polarized fractions (González-Romá & Hernández, 2014; Kozlowski & Klein, 2000). This way, a team splits into behavioral subgroups that share a common perspective (González-Romá & Hernández, 2014). As a consequence, behavioral disagreement creates fault lines among VT members, with team members interacting in opposite directions. This can lead to various types of conflict (Kozlowski & Klein, 2000). Thatcher and Patel (2012) found that fault line formation leads to content and process management conflicts. In addition, it may hinder the development of interpersonal relationships and create distrust, dislike, or disrespect among team members (Thatcher & Patel, 2012). These phenomena were all found to negatively affect the performance of (virtual) teams (Rousseau et al., 2006). We argue that collaborative behavioral consensus reduces (behavioral) fault lines among team members. Team members following a common behavioral orientation refrain from interacting in opposite directions. A common behavioral orientation can prevent VTs from conflicts or interpersonal eruptions. Consequently, collaborative behavior consensus has a positive effect on the performance of VTs. Thus, we hypothesize:

Hypothesis 3a: Collaborative behavior consensus is positively related to the performance of VTs.

Previous studies in different contexts (González-Romá & Hernández, 2014; Uy et al., 2021) have identified multifaceted relationships between the emergence of consensus and the level of the shared within-unit team phenomena (e.g., aggregated mean level). For example, VTs may exhibit a higher level of collaborative behavior (e.g., higher mean level) while exhibiting a higher variance of collaborative behavior (i.e., lack of consensus). Hence, we argue that the relationship between collaborative behavior consensus and VT performance is dependent on the team level of collaborative behavior. High behavioral effort can improve intrateam processes by increasing solidarity or interpersonal openness (Stewart, 2006). Teams with high collaborative behavior interact closely and develop expectations for task completion, which subsequently has a positive effect on performance (Stewart & Barrick, 2000). The end level of team processes (i.e., the level of collaborative behavior at the end of collaboration) has particular relevance for team performance. In a study on entrepreneurial teams, Uy et al. (2021) found that the end level of team processes, toward which the VT members converge, reflects the strength of the teams' motivation for taskwork during collaboration and the teams' willingness to perform the tasks. It acts as amplifying moderator in the relationship between consensus and performance (Uy et al., 2021). Therefore, we argue that the VT's level of collaborative behavior at the end of collaboration, to which the VT members converge, positively moderates the relationship between collaborative behavior consensus and team performance. VTs with higher collaborative behavior at the end of collaboration show a higher motivation or willingness to accomplish tasks. This reinforces the positive link between collaborative behavior consensus and team performance. On this basis, we formulated the following hypothesis:

Hypothesis 3b: The positive relationship between collaborative behavior consensus and the performance of VTs is stronger if the VT's level of collaborative behavior at the end of collaboration (toward which the VT members converge) is higher.

Method

Transparency and Openness

We described our sampling plan, data exclusions (if any), manipulations, and measures in the study and adhered to the Journal of Applied Psychology methodological checklist. The data and codebook are available on the Open Science Framework (link: https://osf.io/2dbcw/?view_only=e52d2ebc9b294faaa215bb56e54db728), while other materials including full correlation matrix can be found in Supplemental Material. The data were analyzed using R Version 4.1.2 (R Core Team, 2021) and the package nlme Version 3.1-152 from the Cran-R-Project (Pinheiro et al., 2021). The design and analysis of this study were not preregistered. The study used (i.e., from the X-Culture project) received ethical approval from the institutional review board at the University of North Carolina at Greensboro (Study name "International Student Collaboration Project: Dynamics and Performance in International Virtual Teams," institutional review board number 11-0260).

Sample and Procedure

To address our hypotheses, we used panel-design data from the X-Culture database (Taras, 2022; Taras et al., 2012). X-Culture is an international business competition that usually involves five to seven students from various countries who are randomly placed in VTs. Students work in VTs during the semester to develop solutions to business challenges presented by corporate partners (e.g., market research and development of a market entry plan). At the end of the projects, all teams submit a consulting report that details the results of the team's market research and managerial recommendations. All project participants are required to complete weekly surveys. This yields a multilevel, multisource, and multiwave database with variables about the collaboration in VTs (see X-Culture, 2023, for a list of publications using the X-Culture database).

We used data collected from early March 2020 to the end of April 2020, which coincided with the first peak of the COVID-19 pandemic, when the strictest lockdowns were implemented. Hence, the individuals worked under an increasing strain caused by the COVID-19 pandemic during the project. Collaboration in the VTs started on March 2. We surveyed the project participants weekly from the end of week 1 (T1; March 8) until week 7 (T7; April 19). The consulting report was graded after the submission deadline (i.e., T8; for a detailed timeline, see the figure in Supplemental Material C). The response rate was 94% throughout the project.

Our data set consisted of 3,506 project participants nested in 703 virtual teams with team members studying in 62 different countries on all continents (see Supplemental Material A, for a detailed list). We considered VTs with at least three team members. Each VT comprised an average of 5.11 students with an international ratio (i.e., team cultural composition) of approximately 60:40 (i.e., 39% of VT members were from the United States and 61% were from the rest of the world). The average age of the team members in the VTs was 21.20 years, and the proportion of men in each VT was 46%. The average educational composition within VTs was 20% postgraduate students (e.g., Master or Master of Business Administration students) and 80% undergraduate students (e.g., Bachelor students). The team members of the VTs had an average work experience of at least 1 year before the project.

Measures

We collected data from multiple sources (i.e., X-Culture and secondary archival data) and at different times (T1–T8) to measure our independent and dependent variables. This multisource and multitime approach to data selection helped us increase the validity of our findings and reduce the exposure to common method bias (Podsakoff et al., 2003).

Collaborative Behavior

We operationalized (task-related) collaborative behavior according to Rousseau et al. (2006) through the three dimensions: coordination, communication, and cooperation. The individuals in the VTs were asked to rate their team members regarding their collaborative behaviors during the project (i.e., round-robin peer ratings). In doing so, for each individual in the VTs, we obtained ratings about the level of collaborative behavior from the other team members' perspectives. We calculated the average of the ratings the team members gave their peers (i.e., an average of peer ratings on collaborative behavior) for every measurement point. Our approach reflects the average level of collaborative behavior for individuali in VTj at timet (the average number of ratings VT members received over time was 3.95). We measured coordination using the average of the peer ratings by the following question: "Did your team members provide team coordination and leadership last week?". The scale ranged from 1 = not at all to 5 = always. Communication was represented by the average peer evaluation of communication between the team members ("Have you communicated with this team member last week?") and measured on a Likert scale from 1 = no communication to 5 = very frequent communication. Wagner (1995) defined cooperation as "the willful contribution of personal effort to the completion of interdependent jobs" (p. 152). We captured cooperation through the average of the peer evaluations of the interindividual effort and helpfulness ("Are your team members working hard and completed assigned tasks last week?"), which was measured on a scale from 1 = does nothing to 5 = works very hard. All items were measured at the end of each project week, from week 1 (T1; after the students had worked on the project for one week), until week 7 (T7). ICC(1) and ICC(2) values were within acceptable ranges (LeBreton & Senter, 2008; for coordination ICC(1) = from .10 to .17 and ICC(2) = from .70 to .85 for the measurement points; for communication ICC(1) = .08 to .19 and ICC(2) = .70 to .83; for cooperation ICC(1) = .11 to .21 and ICC(2) = .76 to .86).

COVID-19 Pandemic

We used external archival data to operationalize COVID-19-related effects and to monitor the extent to which the pandemic (a) caused health threats to the project participants and (b) restricted their access to social exchanges (i.e., COVID-19-related social distancing measures). As the COVID-19 pandemic was a rapidly changing event (especially at the start of the pandemic; Johns Hopkins University, 2020), we used repeated measures to reflect the dynamic nature of the pandemic.

COVID-19 Health Threat. To capture the COVID-19 health threat, we used the number of COVID-19 deaths in the country where the participants studied/lived (Johns Hopkins University, 2020). We calculated the average number of COVID-19 deaths between the start of the collaboration and the end of week 1 (T1), weeks 1 and 2 (T2), and so forth until the end of week 7 (T7). As a result, we obtained seven time points consistent with the time points of our dependent variables. As the data were skewed (e.g., no deaths in some countries at the beginning of the pandemic while other countries already recorded a high number of deaths), we applied a Box-Cox transformation to improve the normality of the distribution (Box & Cox, 1964).

COVID-19 Social Distance. We measured COVID-19-induced social distance using the COVID-19 Stringency Index (Hale et al., 2021). This index considers the degree of social distance the participants were exposed to in the country where they studied/lived during the project. It provides an integrated measure based on nine dimensions, including, for example, workplace and school closures, restriction of internal movements, or travel bans. The scale ranged from 0 = no measures to 100 = strictest measures (Hale et al., 2021). We calculated the average COVID-19 social distance stringency between the start of the collaboration and the end of week 1 (T1), weeks 1 and 2 (T2), and so forth until the end of week 7 (T7).

Team Performance

We measured team performance based on the overall quality of the report submitted by the VTs at T8. Each report was independently evaluated by 5 to 7 experts (e.g., business professors, industry representatives, and trained appraisers). The experts gave their overall evaluation based on the professionalism of the report, the persuasiveness of market research, and the viability of managerial recommendations. The grading scale ranges from 1 = poor to 7 = excellent. To obtain the overall report quality score, the evaluations were averaged across the appraisers.

Control Variables

For the models used to examine Hypotheses 3a and 3b, we included relevant control variables as identified in the previous VTs literature (Mell et al., 2021; Taras et al., 2019). We aggregated all individual-level variables to the team level to obtain average scores for each VT (Taras et al., 2019). Team size is the number of individuals in the VT. Gender composition is the percentage of male team members in the VT. Average age team denotes the average age of the team members in the VT. To operationalize team international study experience and team international work experience, we asked the participants about the total time they worked and studied abroad (Likert scale from 1 = none to 7 = four or more years). We used an item on previous virtual and technical work experiences (“Have you worked on projects that required the use of such tools as Google Docs, Dropbox, Skype, or video conferencing and the like?”) to operationalize team online collaboration experience. The scale ranged from 1 = no experience to 5 = use every day. To evaluate the working language skills (i.e., English) of the team members (i.e., team working language skills), we tested the participants’ English language proficiency skills in a short TOEFL-like test. After the test, the participants were assigned a score between 1 = very low English proficiency skills and 10 = very high English proficiency skills. To account for the international nature of the project, we also controlled for nationality diversity (within each VT) and team cultural intelligence. For the latter, we used the business cultural intelligence quotient (Alon et al., 2016). Individuals had to answer randomly selected cultural intelligence knowledge questions (e.g., “Spanish is the official language in Colombia” or “4 is considered a lucky number in China”) on a true and false basis. The quotient denotes the percentage of correct answers. For nationality diversity, we used the Blau index (Blau, 1977) based on the team members’ home country (Mell et al., 2021). We also controlled for the work experience of the team, as the work experience (1 =

never had a job to 7 = more than 10 years of work experience) within a team may affect team performance (Bernerth & Aguinis, 2016).

In addition, we followed Uy et al. (2021) and included a consensus-related control variable in the models associated with performance. As the VTs had different starting points of collaborative behavior consensus, we controlled for the between-team differences in the level of the collaborative behavior consensus at the start of the project. We estimated the team collaborative behavior similarity at T1 (i.e., the intercept of collaborative behavior consensus) for each VT (Uy et al., 2021). To provide a straightforward interpretation of the score, we reversed the direction of the score by subtracting it from 2 (Sy & Choi, 2013). In this way, a larger score indicates a higher similarity at the start of team collaboration.

Analytical Strategies

To answer Hypothesis 1, Hypotheses 2a and 2b, we used the MGPF (Lang et al., 2019), a form of the consensus emergence model (Lang et al., 2018), which has been employed recently to study consensus in group processes (e.g., Loh et al., 2021; Uy et al., 2021). The MGPF is a three-tier modeling approach that incorporates observations (Level 1) within persons (Level 2) nested in groups (Level 3; see Lang et al., 2019, p. 273, for level-specific equations of the MGPF). The MGPF focuses on analyzing the residual variance within the group across different measurement points to determine whether individuals become (dis)similar in their behaviors over time. A change in residual variance (δ1) signals consensus or divergence. A negative coefficient indicates a decrease in residual variance, which can be interpreted as the emergence of consensus, whereas a positive coefficient signals divergence over time (i.e., dissent). Furthermore, adding person-level predictors to the model provides insights into how specific characteristics of group members (e.g., group members who are differentially affected by COVID-19) promote or hinder the emergence of consensus within their team (Lang et al., 2019). Given the rapidly changing nature of the COVID-19 pandemic (Johns Hopkins University, 2020), we adopted the dynamic approach by Uy et al. (2021) and included time-varying predictors in our models.

We followed the five steps of the MGPF model-building process outlined by Lang et al. (2019). In Step 1, we constructed a model without the emergence of consensus. In Step 2a, we then added the slope variance of collaborative behavior, and in Step 2b, both the slope variance and covariance of collaborative behavior in the model. In Step 3, we modeled the emergence of consensus (δ1) by including the variance of the residuals in the model. In Step 4, we added each COVID-19-related person-level predictor separately in the three-level MGPF model to determine their effects on the slope over time. To assess the effect of each predictor over time (i.e., change in the standard deviation of errors), in Step 5a, we first ran a consensus model with only the main effect of each person-level COVID-19 predictor (with δ2), and in Step 5b, an emergence model including the interaction effect between each person-level COVID-19 predictor and time, while accounting for the effect of each predictor on consensus change (with δ3). In the models, δ2 represents the association of the person-level predictor with the individual's average level of consensus with the rest of the group (i.e., a negative coefficient indicates more individual consensus with the group associated with higher levels of the person-level predictor). δ3 represents whether the person-level predictor is associated with an individual's increasing consensus with the group over time (if δ3 is negative; Lang et al., 2019).

After conducting the MGPF analysis, we used the formula by Lang et al. (2018) to identify the emergence of consensus in collaborative behavior over time by calculating the change in residual variance from T1 to T7 with and without the predictors. We used the Akaike information criterion, Bayesian information criterion, and log-likelihood comparison tests to assess the quality of the models and identify whether consensus emerged (Lang et al., 2018, 2019). To test the potential effect of the person-level COVID-19-related predictors on the emergence of consensus, we estimated likelihood-based R2LR statistics. An increase in R2LR value indicates an increase in the amount of explained variance and, thus, the relevance of the predictor (Lang et al., 2021). To assign a meaningful value to the variable time, we coded T1 as 0 through T7 as 6. Therefore, the intercept can be interpreted as the beginning of collaborative behavior (Singer & Willett, 2003). We used the nlme package in R Version 4.1.2 and the code presented by Lang et al. (2018, 2019, 2021) to estimate our MGPF models and the R2LR. In addition, we followed the analytical procedure by Lang et al. (2019) to handle missing data in all analyses.

To address Hypotheses 3a and 3b, we followed the approach of Uy et al. (2021) and employed their three steps using OLS regression models. First, we included the general control variables in the model (M1). Second, we investigated whether the emergence of consensus in collaborative behavior affects team performance in VTs (M2). On the basis of the MGPF approach, we estimated values for each VT, indicating the VT's individual pattern of collaborative behavior consensus during the project. This value is the slope that reflects the emergence of consensus or dissent, that is, team collaborative behavior consensus (slope). We also reversed the direction of the score by subtracting them from 2 (Sy & Choi, 2013) so that a larger score indicates a greater collaborative behavior consensus over time (Uy et al., 2021). To account for the VT's level of collaborative behavior at the end of collaboration (toward which VT members converge), we included the T7 team aggregated individual collaborative behavior in the model (Uy et al., 2021). Third, to examine the effect of the VT's level of collaborative behavior at the end of collaboration on the relationship between collaborative behavior consensus and team performance, we included an interaction term (i.e., Team Collaborative Behavior Consensus [Slope] × T7 Team Aggregated Individual Collaborative Behavior) in the model (M3). We grand-mean centered the variables included in the interaction term (Uy et al., 2021).

Results

The Emergence of Consensus in Collaborative Behavior in Virtual Teams

Table 1 provides descriptive statistics. Hypothesis 1 stated that VT members converge in their collaborative behavior over time, leading to the emergence of collaborative behavior consensus in VTs. To examine the emergence of consensus for our variables of interest, we compared the different MGPF models (see Table 2). After the $\chi 2$-comparison test, the three-level MGPF models (i.e., M3) for all three variables showed the best model fit. The emergence of consensus is significantly present for all three dependent variables.

The model estimates for Model 3 (M3) are summarized in Table 3. The effect of time on the residual variance was negative for all three variables (coordination: $\delta 1 = -.07$; communication: $\delta 1 = -.10$; cooperation: $\delta 1 = -.03$). Thus, we see that the residual variance changed from .34 (coordination), .50 (communication), and .27 (cooperation) at T1 to .15 (coordination), .15 (communication), and .19 (cooperation) at T7 (see Figure 1). In summary, the results indicate significant evidence that VTs emerge a consensus in collaborative behavior because the within-group residual variance decreased over time. Thus, Hypothesis 1 is confirmed.

The Effect of the COVID-19 Pandemic on the Emergence of Consensus in Collaborative Behavior in Virtual Teams

Hypothesis 2a stated that time negatively moderates the relationship between COVID-19 health threat and collaborative behavior consensus in VTs. Therefore, we continued with the model-building steps and added the person-level predictor of COVID-19 health threat in our MGPF models (Steps 4 and 5). Table 4 presents the results of the model comparison as a formal test for the effect of the predictors on the emergence of consensus. Model 5b (M5b) showed the best fit for coordination and cooperation. By contrast, the predictor showed no effect on the emergence of consensus in collaborative behavior for communication, as the $\chi2$-comparison test result was insignificant for Model 5b (M5b). Thus, COVID-19 health threat is related to the emergence of consensus in collaborative behavior for coordination and cooperation. Table 5 summarizes the MGPF model estimates. We refer to Model 5b (M5b) for all interpretations of the significant results (i.e., coordination and cooperation). We found a negative effect of COVID-19 health threat on residual variance (coordination: $\delta2 = -.14$.; cooperation: $\delta2 = -.10$) and a positive interaction between COVID-19 health threat and time (coordination: $\delta3 = .06$; cooperation: $\delta3 = .04$). To compare how the individuals' exposure a stronger or weaker COVID-19 health threat affect consensus over time, we calculated the residual variance change one standard deviation above the sample mean for the first (T1) and last (T7) measurements and one standard deviation below the sample mean for the first (T1) and last (T7) measurements. This approach provides insights into how individuals affected differently by the predictor differ in the emergence of consensus. As noted by Lang et al. (2019) regarding the interpretation of model estimates, the effect of a person-level predictor refers to the individual's position within the team rather than to the whole group (i.e., the association of predictor with the team members' positions relative to the mean team level). For individuals exposed to a stronger COVID-19 health threat (one standard deviation above the sample mean), there is a residual variance change in coordination from .31 (T1) to .15 (T7) and in cooperation from .25 (T1) to .20 (T7). For individuals exposed to a weaker COVID-19 health threat (one standard deviation below the sample mean), there is a greater change in residual variance from .54 (T1) to .06 (T7) for coordination and from .38 (T1) to .11 (T7) for cooperation (see Figure 2).

This indicates the emergence of collaborative behavior consensus for all individuals exposed to the predictor. However, exposure to a stronger COVID-19 health threat decelerates the emergence of consensus in collaborative behavior for VT members in their VTs, as it is more difficult for them to adapt to the majority behavior (e.g., in coordination and cooperation), or they do not develop consensus at all (e.g., in communication). As an increase in the R2LR values provides additional support for the relevance of the predictor, Hypothesis 2a can be supported.

To examine whether time positively moderates the relationship between COVID-19 social distance and collaborative behavior consensus in VTs (Hypothesis 2b), we repeated Steps 4 and 5 of the MGPF model-building process. We added COVID-19 social distance as a person-level predictor in the model (see Model 6 [M6] to Model 7b [M7b] in Tables 5 and 6).

The model comparison in Table 6 shows that COVID-19 social distance was associated with the emergence of consensus. Thus, COVID-19 social distance was significantly related to the emergence of consensus in collaborative behavior for VT members.

Model 7b (M7b) in Table 5 provides the model estimates. We found a negative effect of COVID-19 social distance on the residual variance (coordination: $\delta2 = -.01$.; communication: $\delta2 = -.01$; cooperation: $\delta2 = -.01$) and a positive interaction between COVID-19 social distance and time (coordination: $\delta 3 = .002$.; communication: $\delta 3 = .002$; cooperation: $\delta 3 = .002$). Therefore, we repeated the calculation of the residual variance change over time (i.e., the same approach as for COVID-19 health threat). Stronger COVID-19 social distance (one standard deviation above the sample mean) leads to a decrease in residual variance (coordination: .53 at T1 to .06 at T7; communication: .54 at T1 to .09 at T7; cooperation: .38 at T1 to .07 at T7), indicating the emergence of consensus. However, individuals exposed to weaker COVID-19 social distance (one standard deviation below the sample mean) showed a similar decrease in residual variance (coordination: .55 at T1 to .06 at T7; communication: .56 at T1 to .09 at T7; cooperation: .40 at T1 to .07 at T7), also indicating the emergence of consensus (see Figure 3).

Despite an increase in R2LR for all variables, individuals exposed to stronger and weaker COVID-19 social distance similarly converge and adapt their collaborative behavior to the majority within their VTs. Therefore, Hypothesis 2b cannot be supported.

The Relationship Between Collaborative Behavior Consensus and VT Performance

To examine the relationship between collaborative behavior consensus and VT performance, we performed OLS regressions (see Table 7).

Hypothesis 3a stated a positive relationship between collaborative behavior consensus and the performance of VTs. The results in Model 2 (M2) showed that coordination consensus (i.e., team coordination consensus [slope]) had a positive and significant effect on team performance ($b = .60$, $SE = .13$, $p < .001$). The values for communication consensus ($b = .05$, $SE = .08$, $p = .522$) and cooperation consensus ($b = -.08$, $SE = .11$, $p = .497$) were insignificant. Thus, only coordination consensus was positively and significantly related to team performance in the VTs, leading to partial support for Hypothesis 3a.

Hypothesis 3b stated that the positive relationship between collaborative behavior consensus and the performance of VTs is stronger if the VT's level of collaborative behavior at the end of collaboration is higher. Therefore, we added the interaction term in the model (see M3 in Table 7). The results showed a negative and significant interaction term for all three variables (interaction for coordination: $b = -.36$, $SE = .16$, $p = .028$; interaction for communication: $b = -.47$, $SE = .16$, $p = .003$; interaction for cooperation: $b = -.65$, $SE = .13$, $p < .001$). We performed simple slopes tests to determine whether collaborative behavior consensus has a differentiated effect on team performance when the VT's level of collaborative behavior at the end of collaboration (i.e., T7 team aggregated individual collaborative behavior) is lower (one standard deviation below the mean) or higher (one standard deviation above the mean). When the VT's level of collaborative behavior at the end of collaboration was lower, collaborative behavior consensus had a positive and significant effect on team performance (coordination: $b = .84$, $SE = .17$, $p < .001$; communication: $b = .42$; $SE = .15$, $p = .005$; cooperation: $b = .31$, $SE = .13$, $p = .021$). These consistent findings indicate that collaborative behavior consensus is crucial for team performance when the VT's level of collaborative behavior (i.e., motivation or willingness of VT members to collaborate) at the end of collaboration is lower. On the contrary, the findings were inconsistent when the VT's end level of collaborative behavior was higher, as coordination consensus positively and significantly affected performance ($b = .47$, $SE = .15$, $p = .001$). If the VT's end level of communication was higher, communication consensus had no significant effect on team performance ($b = -.04$, $SE = .09$, $p = .652$). When the VT's end level of cooperation was higher, cooperation consensus had a negative and significant effect on team performance ($b = -.38$, $SE = .13$, $p = .002$). Whereas it makes sense that collaborative behavior consensus is only partly relevant for performance, when the VT's level of collaborative behavior (i.e., coordination and communication) at the end of collaboration is already higher, the findings for cooperation show the opposite direction. It seems detrimental when VTs have a higher end level of cooperation. We tried to find an explanation for our counterintuitive findings by consulting additional literature. The previous studies have found that free riding (or social loafing) is a relevant factor in VTs (e.g., Furst et al., 1999, 2004; Perry et al., 2016). Thus, we added a variable controlling for potential free riding tendencies in the VTs in our final model (M3) for cooperation (Thomas, 1999; see Supplemental Material B, for a detailed description). Whereas the results (including the simple slopes tests) showed similar scores for all variables included in the analyses, the negative effect of cooperation consensus on the performance of VTs with a higher level of cooperation at the end of collaboration became insignificant. In sum, we conclude that collaborative behavior consensus is particularly important for the performance of VTs with a lower level of collaborative behavior at the end of the collaboration. Therefore, our results lead to a rejection of Hypothesis 3b.

Discussion

Research on the emergence of collaborative behavior consensus, its consequences, and the effects of external crises on VTs is limited. To answer calls to shed light on this topic (Caligiuri et al., 2020; Cronin et al., 2011; Fulmer & Ostroff, 2016), we conducted a study to clarify whether VTs experience an emergence of consensus in collaborative behavior under the impact of an external crisis, using COVID-19 as a specific case. Moreover, we examined how collaborative behavior consensus is related to VT performance. Our results show that VT members converge in their collaborative behavior over time, indicating the emergence of consensus. We identified COVID-19 health threat and COVID-19 social distance as the key facets of the COVID-19 pandemic and provided empirical evidence that individuals' exposure to these facets can have differential effects on their emergence of consensus in collaborative behavior over time. The exposure to stronger COVID-19 health threats largely hindered individuals from developing consensus in collaborative behavior within their VTs. COVID-19 social distance had a minor effect on the emergence of consensus in collaborative behavior. Furthermore, our results show that collaborative behavior consensus (i.e., coordination consensus) is partially positively related to VT performance. Additional moderating analyses revealed that collaborative behavior consensus is particularly important for VTs with a lower level of collaborative behavior at the end of the collaboration.

Theoretical Contributions

This study makes several important contributions to the literature on VTs and the emergence of consensus in behavior. First, whereas previous literature has mainly focused on the convergence of cognition, affections, or emotions (e.g., Fulmer & Ostroff, 2016), we introduce consensus research in the context of behavioral dynamics. We contribute to the open systems theory (Katz & Kahn, 1978) by theoretically and empirically analyzing the emergence processes of collaborative behavior in a VT setting. We demonstrated that collaborative behavior might also be subject to convergence tendencies (i.e., the emergence of consensus). As team members work together to achieve a common goal, their efforts (i.e., collaborative behavior) adjust to a similar level. Individuals develop a shared behavior climate and reciprocally influence each other, thus, leading to behavioral consensus. Therefore, our results add collaborative behavior to the literature on emergence (e.g., Kozlowski & Klein, 2000; Fulmer & Ostroff, 2016; Kozlowski & Chao, 2012;

Kozlowski et al., 2013), that suggested that interactions among individuals can lead to a collective phenomenon (i.e., consensus). We found no statistical support for the fact that the underlying constrained virtual work setting (e.g., time zone differences and limited face-to-face contact; Hertel et al., 2005) inhibits the emergence of consensus in VTs. Even though the VT work environment can negatively affect the collaborative behavior within a team (Mesmer-Magnus & Dechurch, 2009; Ortiz de Guinea et al., 2012), our results indicate that the VTs developed consensus in their behavior (i.e., became similar) over time.

Second, we provide a dynamic multilevel perspective on how collaborative behavior emerges (i.e., the emergence of consensus) over time, and we contribute empirically to the interplay of behavioral processes on three levels, namely time, individual, and team. Previous studies have mainly used indirect quantitative techniques to represent higher level constructs. They aggregated individual-level phenomena to the team level (using cross-sectional research designs; Kozlowski et al., 2013) and assumed that lower level phenomena automatically lead to higher level outcomes. However, these approaches fail to determine the dynamic nature of consensus (e.g., Kozlowski & Chao, 2012). As we used a more advanced statistical technique (i.e., MGPF) to study the process of consensus (Lang et al., 2019) directly (Kozlowski, 2015), we went beyond these approaches. We examined whether behavioral interactions on the individual level led to a consensus or dissent of collaborative behavior as teamwork progressed (i.e., examination of whether collaborative behavior became more or less similar). Thus, we demonstrated and extended our knowledge of how VTs achieve consensus (in collaborative behavior) over time.

Third, by using a phenomenon-driven approach (Hambrick, 2007), we contribute to the (unknown) effects of an external crisis (Cronin et al., 2011; Garro-Abarca et al., 2021; Humphrey & Aime, 2014) in VTs. We theoretically disentangled and empirically tested specific facets of the COVID-19 pandemic (i.e., COVID-19 health threat and COVID-19 social distance) and found evidence that those crisis-related determinants have a differential effect on the emergence of collaborative behavior consensus. In doing so, we enrich the open systems theory (Katz & Kahn, 1978) and continuative literature (e.g., Kozlowski & Chao, 2012; Kozlowski & Klein, 2000) with external (i.e., COVID-19-related) facets that influence VT members' consensus emergence during an external crisis. As a result, our approach adds new insights into the current discussion on the impact of COVID-19 on individuals in a virtual work context (e.g., Lin et al., 2021). Specifically, our research identified COVID-19 health threat as an external factor that could hinder the emergence of consensus in collaborative behavior in VTs. This is in line with the previous research that primarily highlighted crises as disadvantageous for individuals and organizations (e.g., Sweeney, 2008) because crises can damage interactions between individuals, provoke dysfunctional behavior, and disrupt (team)work (Kahn et al., 2013). We found significant but only minor statistical support that COVID-19 social distance has an effect. Although VT work offers a way to interact with individuals experiencing similar stressors in times of COVID-19 (Caligiuri et al., 2020; Kniffin et al., 2021), experiencing stronger and weaker restrictions of in-person contacts had a similar effect on the emergence of collaborative behavior consensus. Taken together, our study suggests that COVID-19 social distance was not critical to the emergence of consensus in VTs.

Fourth, our study showed that collaborative behavior consensus is related to the performance of VTs. Therefore, we are extending the open systems theory (Katz & Kahn, 1978) and literature (González-Romá & Hernández, 2014; Uy et al., 2021) on the effects of emergent phenomena by revealing potential consequences of behavioral consensus in a virtual teamwork setting. Partially in line with our theorizing, we identified that increasing coordination consensus is beneficial for VT outcomes. In this way, our results add new insights into the differentiated effect of fault lines (S. T. Bell, 2007; Thatcher & Patel, 2012) by showing that agreement on how to coordinate taskwork can reduce behavioral fault lines and has a positive effect on team performance. Moreover, we examined the moderating effect of the level of collaborative behavior, thus combining previous literature that focused either on the impact of consensus (e.g., González-Romá & Hernández, 2014) or the level of a shared phenomenon on team performance (e.g., Mathieu et al., 2006). Our results revealed a fine-grained perspective of interaction after controlling for deviant behavioral tendencies (i.e., free riding). Collaborative behavior consensus is particularly important for VTs with lower levels of collaborative behavior at the end of the collaboration. This contrasts our theorizations. A potential explanation could be the timing at which the behavioral dimensions develop their desired effect on performance. VTs with higher levels of collaborative behavior at the end of collaboration might have already encountered difficulties during collaboration. This ensured that their behavior was directed to optimize and fulfill the task (Prince et al., 1997; Rousseau et al., 2006), making behavioral consensus less relevant for performance. In contrast, VTs with lower levels of collaborative behavior had a need for behavioral consensus to compensate for the lack of goal-directedness and optimization of their behavior toward task accomplishment, which they failed to build during teamwork (Rousseau et al., 2006). To conclude, our approach enriches the literature on emergence (e.g., Fulmer & Ostroff, 2016; Kozlowski, 2015; Kozlowski & Chao, 2012; Kozlowski et al., 2013; Uy et al., 2021) by identifying the VTs' level of collaborative behavior at the end of collaboration as a potential moderator. In doing so, we emphasize the relevance of collaborative behavior consensus for VTs with lower levels of collaborative behavior.

Practical Relevance

Our results have significant practical relevance for the management of VTs. First, our study helps managers understand that crises are complex events that have differential effects on the emergence of collaborative behavior consensus in VTs. As an external health threat such as the COVID-19 pandemic can negatively impact the emergence of consensus in collaborative behavior, coordination and cooperation among team members in VTs may be disordered. Therefore, organizations should provide more support to team leaders and members during a crisis to enable effective teamwork. Virtual team-building tools should be implemented to balance, rebuild, and align collaborative tendencies (Holton, 2001), potentially hindered by an external crisis.

Our study also shows that consensus in collaborative behavior is partially positively related to the performance of VTs. This relationship is particularly eminent when the level of collaborative behavior at the end of collaboration is lower, suggesting that collaborative behavior consensus is especially important for VTs with lower levels of interindividual collaboration efforts to still achieve higher quality outcomes. To ensure that VTs continue to collaborate successfully, managers should aim to strengthen consensus in collaborative behavior (i.e., reduction of disagreements) among VTs with collaboration problems. Encouraging the social aspects of teamwork through various activities (Caligiuri et al., 2020), such as virtual coffee breaks or regular team meetings (including discussions), can promote consensus building and increase team performance, even when the willingness to collaborate may be lower.

Limitations and Directions for Future Research

The findings of our study should be considered in light of some limitations, which open avenues for future research. First, our study examined team processes in VTs. We used VTs as a specific context (e.g., Klonek et al., 2022; Taras et al., 2019) for studying the emergence of consensus in collaborative behaviors, the effects of the COVID-19 pandemic, and the consequences of collaborative behavior consensus for VT performance. Our results are, therefore, limited to the context of VTs and COVID-19. Future studies could test whether and how our findings generalize to face-to-face team contexts or compare virtual and face-to-face teams. Moreover, our study hopefully inspires future research to investigate the emergence of consensus and its consequences in different contexts, such as diverse teams and knowledge creation.

Second, our study used the COVID-19 pandemic as a specific example to examine the effect of an external crisis on the emergence of behavioral consensus in VTs. We acknowledge that the elements we identified may be specific to the context of the COVID-19 pandemic. For example, COVID-19 social distance and its associated mechanisms (e.g., lockdowns and restricted physical contact) may not be transferable to other crises (e.g., tornado and flood). Other environmental crises can potentially generate other crises-related characteristics that affect VT collaboration, leading to differential consensus outcomes. VTs in organizations may be directly or indirectly exposed to other external threats (Greenaway & Cruwys, 2019), which may be political (e.g., wars), natural (e.g., natural disasters), or economic (e.g., financial crises). As other environmental threats may have different facets compared to the COVID-19 pandemic, their consequences for the emergence of consensus in VTs remain unclear. Thus, future studies could examine the differential effects of other external threats on the emergence of consensus in collaborative behavior in VTs and other work contexts.

Figures

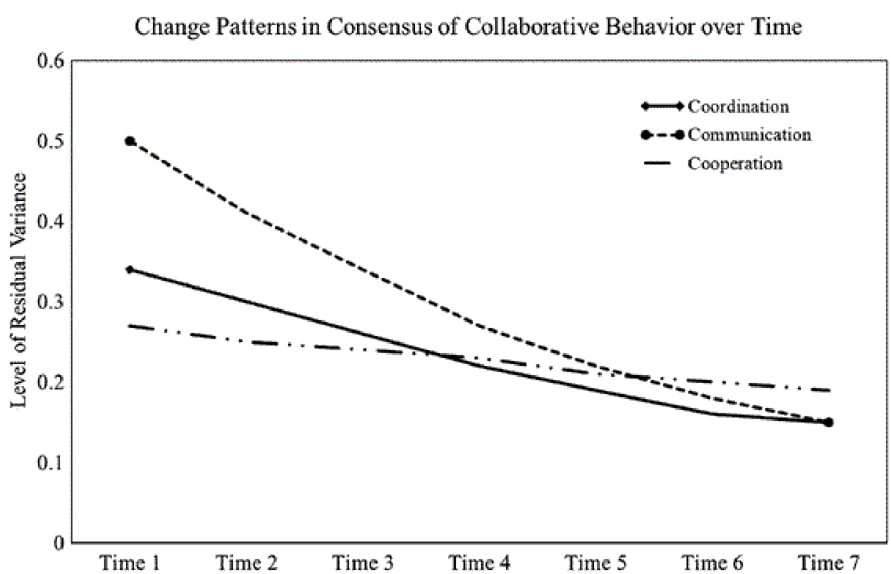

Figure 1. Residual Variance Change of Collaborative Behavior Over Time
Note. Emergence of collaborative behavior consensus in the context of the model specification.

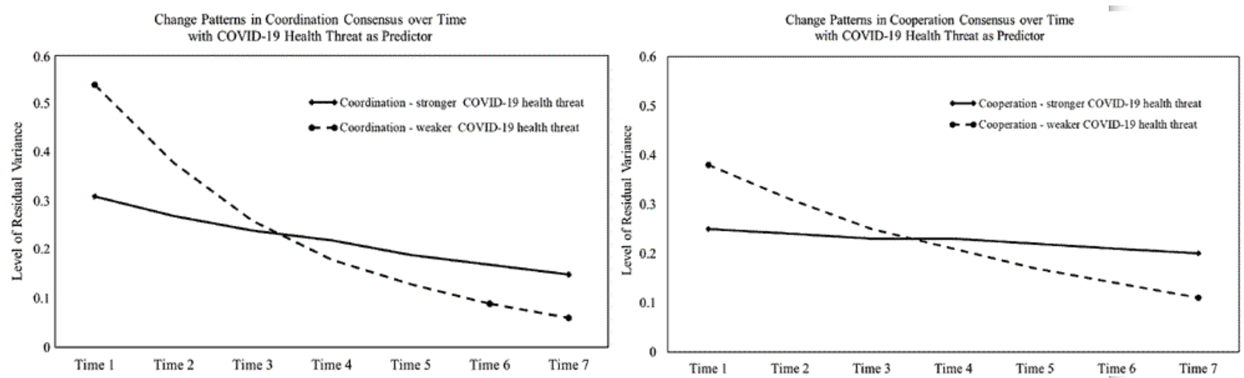

Figure 2. Residual Variance Change of Collaborative Behavior Over Time With COVID-19 Health Threat as Predictor

Note. Emergence of collaborative behavior consensus in the context of the model specification.

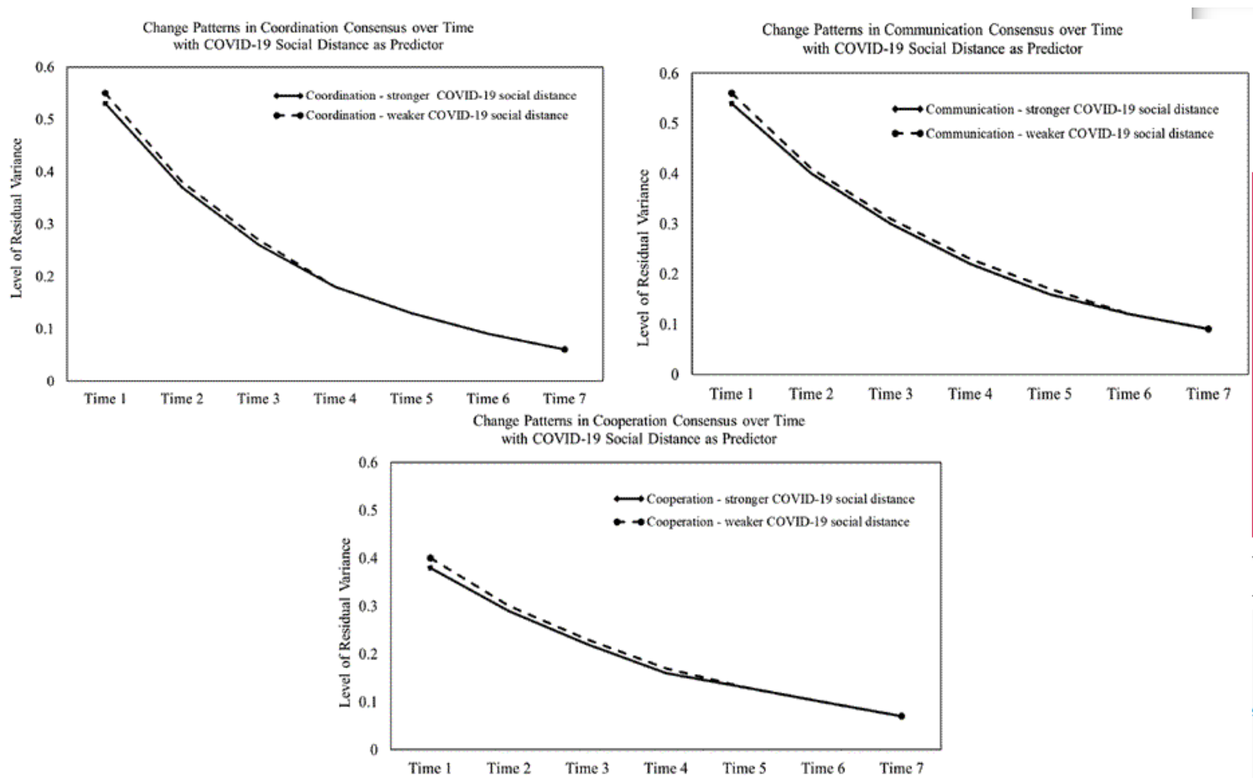

Figure 3. Residual Variance Change of Collaborative Behavior Over Time With COVID-19 Social Distance as Predictor

Note. Emergence of collaborative behavior consensus in the context of the model specification.

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