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Abstract

Mobile collaboration is an emerging kind of collaboration that adopts mobile devices (i.e., laptops, PDAs, and smart phones) and social media software to improve the efficiency and productivity of collaboration. However, many collaborative teams suffer from an anti-social behavior called social loafing. Social loafing will hinder knowledge exchange within the team and further influence team performance and project outcomes. Moreover, the state of an individual's social loafing is unobservable and changes overtime, making it difficult to be identified in real time. Therefore, our research aims to investigate the evolution of social loafing and its impact on knowledge contribution in the mobile collaboration context. We propose a machine learning model to infer individuals' unobserved and evolving social loafing state from the series of task behaviors (quantity and quality of the contributed knowledge). Also, we explore how one's centrality in a social network affects his/her knowledge contribution behavior when he/she is in different social loafing states. We conduct an empirical study and the results show that individuals with high or low social loafing state are very 'sticky' to maintain the previous state and the centrality in the network only positively influences individuals in medium social loafing state. In conclusion, our research adopts a machine leaning method to infer the evolution of individuals' social loafing and provides a comprehensive understanding of knowledge contribution in team work.

Keywords

Knowledge contribution, Mobile collaboration, Network centrality, Anti-social behavior

1. Introduction

Collaboration is very common in a variety of professions and businesses. With the rapid development of telecommunications and computing, many organizations give up offline meetings to discuss their team work within sectors or across sectors and adopt mobile devices (laptops, PDAs, and smart phones) to improve the efficiency and productivity of collaboration (Ali-Hassan et al., 2010; Cheng et al., 2016). Such collaboration based on mobile devices is called mobile collaboration. According to a recent survey by International Data Corporation (IDC), the U.S. mobile worker population is expected to go up steadily from 96.2 million in 2015 to 105.4 million in 2020. By the end of 2020, IDC forecasted that the number of mobile workers will occupy nearly three quarters (72.3%) of the total U.S. workforce. Mobile collaboration has extended to various industries including energy, education, manufacturing, health and insurance. One of the significant features of the mobile collaboration is that individuals can communicate without face to face interaction and exchange knowledge related to team work through mobile devices and social media software. In this case, mobile devices and social media act as collaborative work facilitators in workers' collaboration. Many companies have adopted social media to support mobile collaboration, such as Cozy and Rdio.

Although technology-supported teams (such as social media-supported mobile collaborations) work in a flexible way, many collaborative teams suffer from an anti-social behavior which is called social loafing (Alnuaimi et al., 2010). Social loafing means that individuals tend to reduce motivation and effort in team work compared to individual work, which has negative impact on knowledge sharing (Wasko & Faraj, 2005) and hinder the success of mobile collaboration within company(Suleiman & Watson, 2008). The collaborative technology is perceived to be less useful when there are social loafers in the collaboration; and collective social loafing will negatively influence the teams' potency assessments (Turel & Zhang, 2011). Thus, it is very important for academics and practitioners to recognize and lower individuals' social loafing state in mobile collaboration (Voyles et al., 2015). However, social loafing is a hidden state which is hard to be directly observed by team leaders, and will change overtime during mobile collaboration. Most researchers designed and adopted questionnaires to study social loafing in team work, contributing a lot to collaboration management research (George, 1992; Liden et al., 2004). However, this traditional method is inadequate at studying individuals' real time social loafing and inferring it in the future. Our first research objective aims to recognize individuals' social loafing state by adopting a machine learning method.

A working team is a social network of employees who often collaborate with each other. According to the social network theory, the structure of network will influence individual's social behaviors (Granovetter, 1985). One of the important properties to describe network structure is centrality, which indicates an individual's position in the network and measures linkages between this individual and other people in the same network (Ahuja et al., 2003). Previous studies explored the impact of centrality on knowledge contribution in the collaboration, but no consistent results have been achieved. For example, Wasko and Faraj (2005) shows that workers with high network centrality will contribute more knowledge in the team. However, Zhi and Chang (2009) indicated that medium (neither high or low) centrality is positively related to knowledge contribution. To investigate the reasons behind these contradictory conclusions, the second aim of this study is to understand how one's centrality in a social network affects his/her knowledge contribution behavior by introducing the moderating role of social loafing.

Our research makes some theoretical contributions. First, we adopt a machine learning method to dynamically infer individuals' social loafing that extends the research outputs on static social loafing previously because of the limitation of questionnaires. Second, we enrich the field of knowledge management by unifying the contradictory results about the influence of network centrality on knowledge contribution. For practical implications, our research helps companies reorganize a mobile collaborative group to better exchange knowledge and achieve greater achievements.

2. Literature review

2.1. Social network-based knowledge contribution

A social network is "a set of nodes (individual actors involved in a group) and specific ties between nodes, which can be used to explain the social behavior of these involved individuals" (Mitchell, 1969). Nodes and ties constitute the structure of the network, and the social network theory describes that the network structure will influence individuals' social behaviors (Baker, 1990). Network centrality is an important property of network structure, which indicates one's position in the social network and measures how this individual is linked with others in the same network (Ahuja et al. 2003). Network centrality is a kind of resources for individuals' social actions, providing abundant and positive information (Bizzi, 2017). It will influence how people interact with others in the network and will still affect people's interactions in a different way once the structure changes (Zhang et al., 2008).

In virtual communities, knowledge contribution is one of critical factors to the success of knowledge sharing (Yang & Chen, 2008). Knowledge contribution within sectors or across sectors is very helpful to solve problems and complete tasks. An individual's position in the network influences his/her knowledge contribution behavior (Shuang et al., 2016). Marques et al. (2008) showed that central individual share knowledge amongst themselves and tend to share more knowledge. However, Zhi and Chang (2009) indicated that medium (neither high or low) centrality will be positively related to knowledge contribution. The results of existing research on the role of centrality are contradictory, and there are few studies on how centrality affects individuals' knowledge contribution behavior.

Wasko and Faraj (2005) showed that quality and quantity are two basic parts of knowledge contribution. For mobile collaborative teams within the company, quantity alone is not enough to complete the task and the quality of the contributed knowledge is more important sometimes. However, most previous studies about knowledge contribution focused only on the quantity and ignored the quality of the knowledge (Kankanhalli et al., 2005; Ma & Agarwal, 2007).

2.2. Anti-social behavior and social identity in mobile collaboration

Social loafing refers that individuals will withhold his/her effort when they are working in a team compared with working individually (Chidambaram & Lai, 2005) and it is an anti-social behavior (Alnuaimi et al., 2010). Researches have approved the existence of social loafing in a variety of tasks such as brainstorming, shouting, or rope pulling, its antecedents and effects within the laboratory, classroom, especially in the workplace (Karau & Williams, 1994; Piezon & Ferree, 2008). Hernandez et al. (2010) created a construct, called knowledge withholding (the likelihood that individuals contribute less knowledge in the collaboration than they could), and analyze the antecedents of it. Social loafing has negative influence on team performance and outcomes (Karau & Williams, 1994) . In the recent years, researchers have turned to focus on the social loafing in online team, Alnuaimi et al. (2010) found that social loafing exists in technology-supported teams. Moreover, Turel and Zhang (2011) found that collaborative technology will be perceived less useful if there are social loafers in the collaboration.

Social loafing is identified as a moderator which indirectly influence knowledge contribution behavior in technology-supported distributed teams. For those in the higher level of social loafing, they will perceive a less valued outcomes which makes it more difficult to motivate them to compensate for the poor team performance (Hart et al., 2004). For this reason, increasing their network centrality (a kind of resources for their social action) may have less influence on knowledge contribution in the collaboration. And there are few researches directly exploring the moderating role of social loafing. Social loafing is a hidden state which is hard to be observed directly. Many previous researchers adopted questionnaires to study social loafing in team work (George, 1992; Liden et al., 2004). This traditional method has some limitations, such as being inadequate at studying individuals' real time social loafing.

Individuals' social loafing state can be indicated from their behaviors in collaboration (e.g., knowledge contribution) based on the social identity theory. Individuals' task behavior will indicate their unobserved self-identities (posters or lurkers) (Ashforth, 2001). Tajfel and Turner (1986) gave the definition of social identity as "the individual knows that he belongs to certain social groups and influence his group members in terms of emotion and value". Bergami and Bagozzi (2000) indicated that individuals will categorize themselves into specific group according to the cognitive dimension of social identity theory. Specifically, in the team work, individuals will define themselves as contributor or lurker with different social loafing state, and these roles will guide their behaviors which is line with their self-identities (Bruijn et al., 2012). Moreover, Ashforth (2001) pointed that task behaviors (quantity and quality of contributed knowledge) can serve as the observable indicators of self-identity (posters and lurkers).

3. Machine learning model for anti-social behavior in mobile collaboration

Zhang et al. (2017) proposed a conceptual S-O-R framework to explain anti-social behavior states in collaboration. Developed from the above framework, in this paper, we further conducted an empirical study to examine the transitional possibility of participants between different social loafing states in mobile collaboration. This study uses previous individuals' knowledge contribution to analyze the dynamically social loafing in mobile collaboration, and our model has two features: (1) infer the evolution of social loafing during the process of collaboration, (2) account for the influence of network centrality on knowledge contribution and the moderating role of social loafing.

Figure 1 shows how our model works. In the period t, an individual belongs to a social loafing state with a probability, 0 representing the lowest social loafing state and n representing the highest state. This member is influenced by the environmental condition in t and choose to move to a higher state, keep the same state or become a lower state in the period t+1. Then, his/her social loafing state in the period t+1 determine several knowledge contribution behaviors with different probability. He/she is also influenced by the environmental condition in t+1 which will cause the change or maintain of their social loafing state in the period t+2. Figure 2 is our theory framework which is based on social network theory and social identity theory. Individuals' centrality will influence their knowledge contribution and the relationship is moderated by the social loafing state.

4. Empirical application

4.1. Data description

We collected real world behavioral data from a mobile collaboration project in China. At the beginning of the experiment, all participants were divided into 10 mobile collaboration teams. Each team was assigned a team work different from other teams' work at the beginning, and they had to finish it by the end of the project. Participants were required to discuss their task through social media APPs at mobile device (lagtop, PDAs, and smart phones). In this case, we downloaded their chat contents in three time periods, then our data set has 4137 chat contents. Table 1 is the detailed description of data.

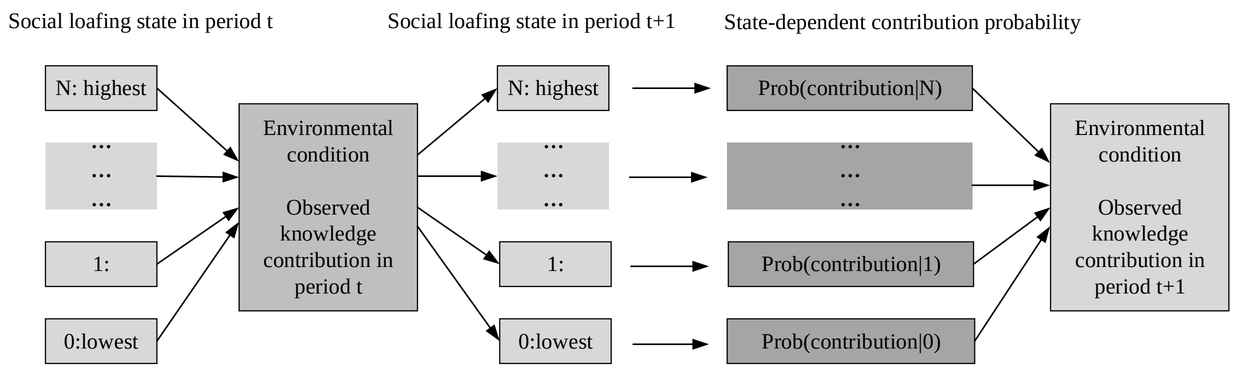

Fig 1: Machine learning model in our research

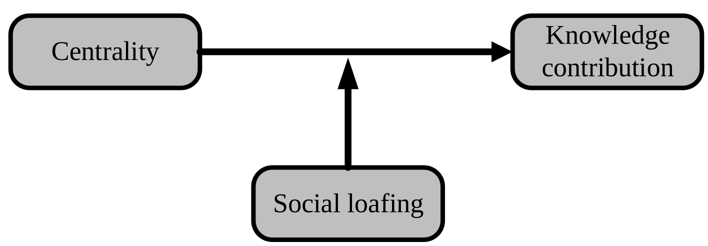

Fig 2: Our research framework

4.2. Variables description

In this section, we describe the variables used in the research model. Succinct definition of these variables are provided in Table 2.

$RecordNum_t$: $RecordNum_t$ is a count variable, when a participant send a message through social media in a session, his/her record will be added 1 in this session. In this study, we divided the whole period of the course into three sections. $Record_t$ represents the number of messages sent by a participant during the period between time t and time t+1, t=0, 1, 2. And we use the $LgRecord_t$ to do regression analysis.

$RecordQua_t$: $RecordQua_t$ is a continuous variable which measures the quality of knowledge contributed by participants. During the period between time t and time t+1, we calculate the sum of products of weight and normalized number of different kinds of chat contents, called $RecordQua_t$.

Centrality: In this paper, a participant's centrality means the eigenvector centrality, which is the sum of centralities of other nodes to which they are linked, and the weight is the strength of connection (Bonacich, 1972). In the social network, we use minimum method to symmetrize symmetric ties (Borgatti et al., 2002), in which the connecting strength between A and B is determined by the smaller connecting strength from A to B and B to A. Formally, eigenvector centrality is the principal eigenvector of the network data matrix C, where c_{ij} represents the strength of the tie from node i to node j. An eigenvector x meets the equation $\lambda x = Cx$, where λ is the eigenvalue of x. The largest λ correspond with the principal eigenvector. We use UCINET to analyze these collected data (Borgatti et al., 2002), calculating individual eigenvector centrality scores.

Data	The number of data (number and percentage)									
Total number of chat contents	4137									
Three period	First			Second				Third		
Number	3340			508				289		
Percentage	80.73%			12.28%				6.99%		
Team name	1	2	3	4	5	6	7	8	9	10
Number of participants	16	16	16	16	15	15	16	15	15	15
Number of chatting contents	548	42	758	355	254	732	544	0	386	518
Percentage of chatting contents	13.25%	1.02%	18.32%	8.58%	6.14%	17.69%	13.15%	0%	9.33%	12.52%

Table 01: Data description

Variables	Types	Definition
Centrality	Continuous	The disparity in eigenvector centralities between nodes
$RecordNum_t$	Count	The number of messages sent by a participant during the period between time t and time t+1. (t=0,1,2)
$LgRecordNum_t$	Continuous	The logarithm of $Record_t$ to base 10.(t=0,1,2)
$RecordQua_t$	Continuous	The sum of the weighted sum of the records of each participant between time t and time t+1. (t=0,1,2)

Table 02: Model variables

4.3. Text analysis of messages

We define a session for a period of information exchange between persons. Each observation contains a person's chat contents, uploading downloading records. Then, we use text analysis to infer each person's contribution during each session and the method used for each session is the same. During model building, we use Jieba Chinese NLP module in Python to divide these chat contents into words. Then, we count the number of different words as the vector of one chat content and use TF-IDF algorithm to extract the word matrix to make feature matrix (BaezaYates et al., 1999). In the next step, we use Bayesian algorithm to make classification (Tirunillai & Tellis, 2011). In order to count the number of different kinds of chat contents of each person, we use previous tables of chats and PivotTable. As a result of the classification process we obtain the number of different kinds of chat contents for each person and normalize them. Finally, we set up weights for each classification of chat contents respectively. Each person will get a score by summing products of weight and normalized number of different kinds of chat contents. We classify people into low, medium and high engagement in the collaboration according to their score, which is represented by 0, 1, 2 respectively.

As for chat contents, through the classification model we divided them into three or two categories: high, medium and low or high and low. We use chat contents from 1^{th}, 6^{th}, 10^{th} team as the training dataset and we label these chat contents by hand. Then we use the classification model to train these two cases separately and obtain their accuracy, recall and F1-scores, which are shown in Table 3.

Model	Number of kinds	Accuracy	Recall	F1-score
Classification Model	2	0.706	0.687	0.669
	3	0.770	0.772	0.753

Table 03: Results of comparison of three-kind and two-kind Case

As shown in Table 3, the three-kind classification model is better than two-kind model on accuracy, recall and F1-score. So, we choose the three-kind model. Then, we explain the detailed process and results of this case. We divide chat contents into three categories--high, medium and low, with counts 2478, 949 and 710. After that, we divide them into three period of time so there are three categories in each session. According to the result of classification of chat content of each session, we get the number of chat contents of each participant and then normalize the number, which means the scores is equal to the count of chatting contents in each team divided by the count of chat contents of each participant in this team. Finally, we get the result of each participant in each session through the weight of chat contents of different kinds and the threshold. The final results of participants' classification is shown in Table 4.

	High	Medium	Low
Session1	47	45	46
Session2	47	18	73
Session3	47	3	72

Table 04: Results of participants' classification

There are 47 participants of high status, 46 participants of medium status and 45 participants of low status in session 1. There are 47 participants of high status and 91 participants of medium status in session2. There are 47 participants of high status and 75 participants of medium status in session 3. Because there are no chat contents of team 7 in session 3, the number of participants in session 3 is smaller than other two sessions.

4.4. Estimation results

4.4.1. Selecting the number of states

The first step in estimating the model is choosing the number of states by model selection measures. Greene and Hensher (2003) suggest to use Bayesian Information Criterion (BIC) to compare models with different states and decide which number is better.

$$\mathrm{BIC} = \ln Likelihood\ - Size * \ln(Par)/2 \tag{1}$$

In the equation, Size is the total number of parameters in the model and Par is the quantity of participants. We estimated 2 models imposing a different number of states at a time. Two states includes low and high social loafing. Three states include low, medium and high social loafing. These two scenarios are run separately and we get each of their log-likelihood values. The results are shown in Table 5. According to the BIC, the three-state model performs better.

Model	Number of states	Log-likelihood	BIC	Variables estimate
HMM	2	-534.835	-703.809	12
	3	-431.591	-638.619	21

Table 05: Comparison of models

4.4.2. Model estimates

Table 6 is the A matrix in model mentioned before which summarizes the estimation results for the three intent states. At the beginning, most participants (77.48%) are in the medium social loafing state and one quarter of the whole participant group (21.96%) is in the low state. High state is extremely ‘sticky’ (98.44%), that is once a participant moves up to the high social loafing state, he/she is more likely to keep this state, while low state is ‘sticky’ (75.15%) as well. There is 69.61% probability of jumping from medium state to high state if a jump occurs, while jumping from medium to high is only at 4.46% probability.

t - t+1		Low state	Medium state	High state
Starting probabilities		21.96%	77.48%	0.56%
Transition Matrix	**Low state**	75.15%	0.26%	24.59%
	Medium state	4.46%	25.93%	69.61%
	High state	1.08%	0.48%	98.44%

Table 06: Estimates for the three-state model

Table 7 is the B matrix in model mentioned before which shows the possibility of a participant’s engagement in the team work under different social loafing state. Participant with high, medium or low social loafing sate are more likely to keep low (75.03%), medium (40.85%) or high (89.63%) engagement in a team work respectively. On the other hand, about 40.4% participants with medium social loafing state tend to be involved in the low engagement in the collaboration and 23.07% participants with high state tend to behave high engagement.

t	Low engagement	Medium engagement	High engagement
Low state	4.07%	6.30%	89.63%
Medium state	40.4%	40.85%	18.75%
High state	75.03%	1.90%	23.07%

Table 07: Emission matrix

4.4.3. Regression analysis

We use a linear regression model to analyze how an individual's centrality influences the quantity and quality of messages sending of him/her when they are in different types of social loafing state.

$$\mathrm{LgRecordNum}_t = \alpha_1 + \beta_1 * Centrality + \varepsilon_1 \tag{2}$$

$$\mathrm{Record}_t = \alpha_2 + \beta_2 * Centrality + \varepsilon_2 \tag{3}$$

The results for the impact of centrality on messages sending are in Table 8. From the intercept estimates, we find as expected that individuals with low social loafing state are more likely to send more messages with higher quality. However, the centrality will only positively and significantly influence the quantity and quality of knowledge shared by individuals with medium social loafing state.

Variables	**High social loafing state**		**Medium social loafing state**		**Low social loafing state**	
Quality(Qi) Quantity(Qt)	Qi	Qt	Qi	Qt	Qi	Qt
interception	-0.06	-0.17	-0.01	0.41	0.76	1.08
centrality	0.38	1.52	0.19*	1.99*	0.35	0.97

Table 08: Results of linear regression model

5. Discussion

Figure 3 shows the social loafing state transition probability. At the beginning, nearly 77.48% individuals are in medium social loafing state. And there is a 69.61% probability of jumping from medium state to high state if a jump occurs, which means it is more likely for them to perform even worse. Most social loafing behaviors occur for team members feel that they cannot get rewards matching their efforts. If their efforts are not discriminated from others', they may tend to conduct social loafing behaviors. In the dataset in our study, members in one team will get similar final scores given by the instructor, which doesn't adequately reflect different efforts. For this reason, most participants in medium social loafing state choose to jump to higher state and spend less effort.

Figure 4 shows the knowledge contribution behavior that are chose by participants when they are in different social loafing states. If someone contributes more quantity of and more relevant knowledge, he/she is more engaged in the mobile collaboration. Individuals with high, medium and low social loafing will have low, medium and high engagement respectively.

Individuals who are in the central position of the network will have stronger relationships with others which can increase the amount and diversity of resources that they can get (Stam & Elfring, 2008). Thus, they can learn more about their tasks and get help from other members easily, finding opportunities to make a contribution.

As suggested by the result of regression model, only participants with medium social loafing state can be positively influenced by network centrality. The reason is that both individuals with high and low state are very sticky. For those in the high state, the task exceeds their current ability. Increasing their connections with others hardly strengthens their ability. For those in low state, they are capable enough so that they do not need information from others, or they are already in the central position. Individuals in medium state are self-motivated to study and improve their ability but they also need help from others, that's why improving their network centrality helps them contribute more knowledge with greater quality.

6. Implications and Conclusion

In this paper, we develop a machine learning model to infer social loafing evolution in the mobile collaboration. We get available data from social media platforms and questionnaires. We identify three-state model, which reveals internal structures underlying social loafing dynamics. We also examine the transitional possibility of participants between 3 states and the how network centrality influences the quality and quantity of knowledge contributed by individuals in different social loafing state.

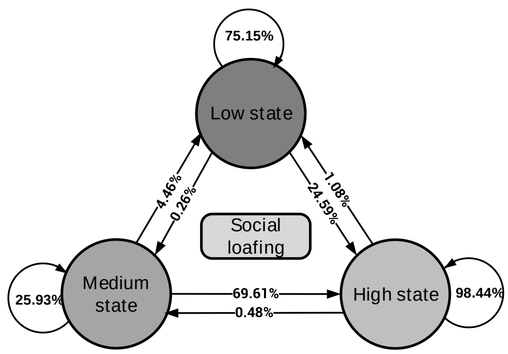

Fig 3: Social loafing state transition

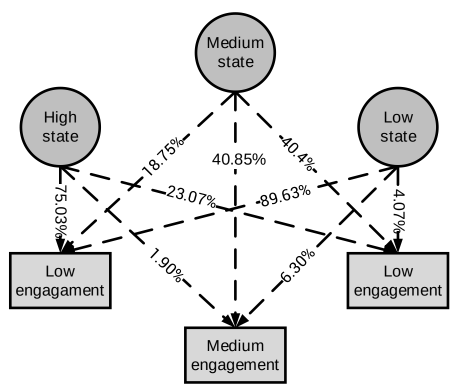

Fig 4: Probability of engagement under different social loafing state

For theoretical implications, we infer the evolution of social loafing states which is regarded as a static notion previously. We unify the contradictory results about the influence of social capital on knowledge contribution by examining the moderating role of social loafing.

For practical implications, this study helps companies re-organize a mobile collaborative team to exchange knowledge better. In a mobile collaboration in real industry, most team members are in medium social loafing state, and it is much easier to motivate them to behave better compared to motivating those with high social loafing state. For those who are in medium state, improving their centrality in the network and giving them opportunities to build connections with other members help them contribute more knowledge with greater quality. In terms of the design of social media within company, functions of inferring individuals' social loafing state by knowledge contribution behaviors should be added. After the identification, the software can automatically recommend team members to those individuals in medium social loafing state, which can help them get more connections and move them from the edge to the center in the social network.

There are two main limitations of this study. First, the text analysis is not automatic enough. In the future research, we will increase the quantity of data and choose other text classification model such as SVM and so on. Through this way, we can compare the different results calculated by different models to choose the best one. Secondly, we only consider the eigenvector centrality which measure one's interaction with others in their team. In the future, we tend to consider other types of centrality, such as interactions with skilled individuals within team or interactions with others out of the team.

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