Organizational Learning in the Age of Work-From-Home

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With the repeated resurgence of the coronavirus, many organizations have had to consider policies for limiting the gathering of their employees so as to contain the spread of the virus. Faced with the need for social distancing, many organizations have adopted virtual platforms and taking turns to work-from-home (WFH) to ensure the operational continuity. Most organizations have adopted these measures somewhat passively, i.e., when the government announces mandatory limitation of gathering, they simply follow the government mandates, and maintain basic operations while awaiting the lifting of the ban. Although organizational members are forced to work-from-home entirely or take turns to work-at-the-office (WAO), the trade-offs between effective exploration and exploitation in organizational learning may still be supported by virtual platform and information technology (Sturm et al., 2021).

Since a passive response might cause low collaboration efficiency and ineffective organizational learning when spontaneous communications that spur serendipitous innovations decrease (Bernstein et al., 2020), it might be useful to consider an active and strategic response. More precisely, if an organization is able to discover what proportions of members should WFH; how to design the WFH shifts; and whether investing in IT for more effective communication and collaboration might reduce the detrimental effects of WFH, then the organization might be able to achieve superior organizational learning outcomes.

In order to better understand the impact of WFH practices on organizational learning, we extend March's (1991) classical model of exploration and exploitation while incorporating the notions of explicit and tacit knowledge from Miller (2006) and consider shift arrangements that would alter the transfer of explicit and tacit knowledge among members. The need to incorporate knowledge tacitness is that only partial tacit knowledge can be converted to explicit knowledge and knowledge is never fully explicit in organizational routines (Nonaka and Takeuchi, 1995).

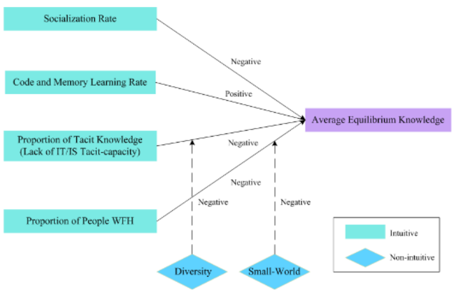
A Model of Organizational Learning with Work-From-Home (WFH)

Our model is an extension of March's (1991) classical model of organizational learning. The setup consisting of an m-dimensional vector for environment and agents' beliefs and n members (or agents) are consistent with March. We incorporate the distinction between explicit and tacit knowledge following Miller et al. (2006) where a proportion q of the environment and agents' beliefs are denoted as tacit. More precisely, the m-dimensional belief contains explicit and tacit dimension. For instance, the organization generates organizational code (i.e., mediation of explicit knowledge) and memory (i.e., mediation of tacit knowledge) reflecting the collective knowledge and wisdom of the organization (Paoli and Prencipe, 2003; Miller and Martignoni, 2016).

As we acknowledge the presence of tacit knowledge in organizational learning but do not consider the distance among individuals, we conceptualize organizational learning as learning from the code, from memory, learning by the code and by memory as adding memory enables the transmission of tacit knowledge. Thus, the probability of agents learning from the code and memory is defined as p_1 and the probability of learning by code and memory is defined as p_2. Unlike those agents in the WFH arrangement who can only access the explicit knowledge components of the organizational code, individuals in the WAO arrangement are able to acquire and disseminate both explicit and tacit knowledge (Borgatti and Cross, 2003; Miller et al., 2006; Schilling and Fang, 2014). Besides, as we define q as the proportion of tacit knowledge, in WFH arrangement only $(m–q\times m)$ dimensions of agents' beliefs and the organizational code can adapt whereas $(q\times m)$ dimensions of agents' beliefs and organizational memory related to tacit knowledge remain constant, but all m dimensions of agents' beliefs and the organization code and memory can adapt in the WAO arrangement.

Our model initially adds three shift arrangements s (indexed by 1, 2 or 3), because when dealing with gathering limitations, some portions of organizational members are allowed to WAO while the rest are required to WFH. Thus, the proportion of members in the WFH arrangement is defined as wfh. For instance, wfh=0.25 means that 25% of organizational members are in the WFH arrangement whereas the rest (75%) are WAO. To better simulate the work scenarios, we equally divide WFH and WAO individuals into two groups, respectively, as sub-group divisions may provide an opportunity to balance the exploration and exploitation trade-off (March, 2004; Fang et al., 2010; Schilling and Fang, 2014). Specifically, each WFH group has $(n\times wfh)/2$ agents, and each WAO group has $(n–n\times wfh)/2$ agents. Suppose that we have four sub-groups with a proportion of wfh, they could be initialized as A=$Group_1^{H}$, B=$Group_2^{H}$, C=$Group_1^{O}$ and D=$Group_2^{O}$, where superscripts H and O denote "Home" and "Office", respectively.

Shift 1	$Group_1^H$	$Group_2^H$	$Group_1^O$	$Group_2^O$
turn 1	A	B	C	D
turn 2	C	D	A	B
Shift 2	$Group_1^H$	$Group_2^H$	$Group_1^O$	$Group_2^O$
turn 1	A	B	C	D
turn 2	B	C	D	A
turn 3	C	D	A	B
turn 4	D	A	B	C
Shift 3	$Group_1^H$	$Group_2^H$	$Group_1^O$	$Group_2^O$
turn 1	A	B	C	D
turn 2	B	C	D	A
turn 3	C	D	A	B
turn 4	D	A	B	C
turn 5	A	C	B	D
turn 6	B	D	A	C



In table, shift 1 is a non-contact scheduling method with no overlap and face-to-face contact between the initialized home and office subgroups. Thereby the face-to-face interactions between A and C, A and D, B and C and B and D will be absent. This scheduling method has a cycle of two days. Shift 2, with a cycle of four days, is a partial-contact scheduling method where there is partial overlap between the home and office subgroups. C and D, D and A, A and B, and B and C have face-to-face interaction, but the face-to-face interaction among subgroups A and C and B and D will be absent. And, shift 3 is a full-contact scheduling method with complete overlap between the home and office subgroups. Every group pair has face-to-face interaction within the six-day cycle.

Results

The model described above was implemented in MATLAB R2018b. There are five major parameters – p_1, p_2, *wfh*, q and s in the model where m was set as 30, n as 80, and simulation runs (i.e., time periods t) as 80 following March (1991). For each run, the average equilibrium knowledge level of all agents during each period t=0, …, T were tracked. Equilibrium occurred when all agents had the same explicit beliefs. Three regression results have been visualized in the figure above. In multivariate linear regression, the coefficients of s_1 and s_3 are 0.001 (p<0.1) and 0.002 (p<0.05), respectively, which indicate that compared with shift 2 (s_2), shift 1 produces better outcome and shift 3 generates the best outcomes. Moreover, the result of q for the main and covariates models (q =-0.069, p<0.001) shows that with greater proportion of tacit knowledge, the average equilibrium knowledge would face a decline.

In a second set of multivariate regression analyses that considered the interaction effects of knowledge tacitness (q) and the learning parameters (p_1 and p_2), we find that for organizations using shift 1, the interaction effect between p_1 and q is insignificant (p=0.624), but this interaction effects for organizations adopting shifts 2 or 3 are significant (p<0.001), and the coefficients of shifts 2 and 3 are -0.027 and -0.028, respectively. This suggests that with an increase in the proportion of tacit knowledge, the negative effect of rapid learning from code/memory (p_1) on average equilibrium knowledge could be enhanced when adopting either shift 2 or 3.

In a third multivariate linear regression analysis, we considered the proportion of individuals working from home (*wfh*) and found it to be significantly and negatively related to average equilibrium knowledge in all three shifts (p<0.001). These results are consistent with the numerous studies that show that productivity drops following large-scale changes, such as a pandemic (Bernstein et al., 2020). Moreover, the interaction effects between learning from code/memory (p_1) and proportion of members working from home (*wfh*) is not significant for shift 3 (p=0.538) but is negative and significant for both shifts 1 and 2 (p<0.001) and the coefficients are -0.019 and -0.017, respectively. Since the main effect of p_1 on average equilibrium knowledge is negative when adopting shifts 1 or 2, the $p_1 \times wfh$ interaction effects indicate that for an organization adopting shift 1 or 2, when the proportion of members working from home increases, the negative influence of fast socialization on average equilibrium knowledge would be enhanced, which means p_1 and *wfh* are complementary for shifts 1 and 2. Furthermore, the interaction effect of the proportion of members working from home (*wfh*) on learning by code/memory (p_2) is insignificant for shift 2 (p=0.397), while this interaction effect is significant and positive for shifts 1 and 3 with the coefficient 0.023 (p<0.001) and 0.014 (p<0.05), respectively. Since the main effect of learning by code/memory (p_1) on average equilibrium knowledge is positive when adopting shift 1 or 3, the results suggest that when the proportion of WFH members in shifts 1 and 3 increases, the positive impact of fast learning by code/memory on average equilibrium knowledge would be enhanced.

Discussion

Coordinating WAO and WFH groups has become an important management issue. In order to explore the implications on organizational learning in the age of work-from-home, our model extends March's (1991) and Miller et al.' s (2006) classical exploration-exploitation models to incorporate shifts arrangements. The scenario that inspires us to add shift arrangements to the model is that parts of agents are allowed to work at the office while the rest are forced to work from home due to gathering limitation. Even though, adding tacit knowledge to the classical model has been done by Miller et al. (2006) who claimed that interpersonal exchange related to tacit knowledge requires mutual interactions between individuals, our model adopts a broader perspective. While adhering to Miller et al.'s viewpoint of interpersonal exchange, we posit that tacit knowledge could be exchanged by mutual learning, group discussion memory (Kumar and Dutta, 2017) and transactive memory systems (Zhao and Gao, 2014).

Diversity, as a central factor in the problem of organizational adaptation in March's model (1991), has been extended in our model to not only the intra-organization and static inter-organization factors (Fang et al., 2010), but also the dynamic inter-organization factors when considering shift arrangements. Except for learning rate and turnover of personnel (March, 1991), which helps to preserve diversity, Fang et al. (2010) who added Watt's "connected caveman" model as a static structural design to March's model, claimed that moderate cross-group linkages could also preserve diversity for codified knowledge; March (2004) who divided the organization into subgroups believed that structural designs such as subgroup divisions help to maintain the balance between exploration and exploitation owing to the diversity for codified knowledge (March, 2004); and those who considered the effects of time argued that intermittent breaks (Bernstein et al., 2018) in interaction and social influence and outside disruption (Xiao et al., 2021) in technological innovation could improve collective intelligence since constant influence, such as storing solutions for quick recall, would decrease the diversity and hinder exploration. Inspired by the intra-organization diversity, static inter-organization diversity for codified explicit knowledge and the effects of time, our model initially proposes that dynamic shift arrangements could generate dynamic inter-organization diversity for tacit knowledge. More precisely, the diversity generated by non-contact scheduling methods would not only substitute the diversity loss caused by rapid learning (i.e., exploitation), but also accelerate interpersonal exchange, such as the development of transactive memory systems and organization memory, which may partially overcome the challenges of greater tacitness.

The small-world effect had a positive impact on average knowledge outcomes when considering interpersonal exchanges in the exploration-exploitation model. Miller et al. (2006) added local and distant search in the model when considering interpersonal mutual learning, and argued that rapid distant learning (i.e., system-wide exploitation) can turn great geographical distances into a small world. Fang et al. (2010) from the perspective of structural design, proposed that semi-isolated subgroups offer the "best of both worlds" in information diffusion and learning, as isolation could preserve variety for learning but hinder the densely clustering from small worlds. Except for the small-world connectivity provided by interpersonal mutual learning and structural design, our modeling and simulation results show that the full-contact scheduling approach for shift arrangements can also generate small-world effects without sacrificing the diversity provided by structural isolation, fast rate of distant learning and slow rate of codification. Specifically, even though organizations might have limited distant search due to ineffective IT support and fixed isolated subgroups, the small-world effect could also occur when adopting full-contact scheduling for shift arrangements. The full-contact scheduling method in the office can not only partially preserve diversity, but also promote empathy, spontaneous communication (Hinds and Mortensen, 2005), perception of involvement, interaction intensity which are conventionally particular to collocated scenarios (Ensmann et al., 2021), and thus could promote the organizational learning of tacit knowledge in remote work.

References

[1] Bernstein, E., Shore, J., and Lazer, D. (2018). How intermittent breaks in interaction improve collective intelligence. *Proceedings of the national academy of sciences*, 115(35), 8734-8439.

[2] Bernstein, E., Blunden, H., Brodsky, A., Sohn, W., and Waber, B. (2020). The implications of working without an office. *Harvard business review*, 1-14.

[3] Borgatti, S. P. and Cross, R. (2003). A relational view of information seeking and learning in social networks. *Management science*, 49(4), 432-445.

[4] Ensmann, S., Whiteside, A., Gomez-Vasquez, L., and Sturgill, R. (2021). Connections before curriculum: the role of social presence during Covid-19 emergency remote learning for students. *Online learning journal*, 25(3).

[5] Fang, C., Lee, J., and Schilling, M.A. (2010). Balancing exploration and exploitation through structural design: the isolation of subgroups and organizational learning. *Organization science*, 21(3), 625-642.

[6] Hinds, P.J. and Mortensen, M. (2005). Understanding conflict in geographically distributed teams: the moderating effects of shared identity, shared context, and spontaneous communication. *Organization science*, 16(3), 290-307.

[7] Kumar, A. and Dutta, S.K. (2017). Tacit knowledge transfer in coopetition: an empirical investigation of the role of business group affiliation. *Journal of strategy and management*, 10(4), 453-468.

[8] March, J.G. (1991). Exploration and exploitation in organizational learning. *Organization science*, 2(1).

[9] March, J.G. (2004). Parochialism in the evolution of a research community: the case of organization studies. *Management and organization review*, 1(1), 5-22.

[10] Miller, K.D. and Martignoni, D. (2016). Organizational learning with forgetting: reconsidering the exploration-exploitation tradeoff. *Strategic organization*, 14, 53-72.

[11] Miller, K.D., Zhao, M., and Calantone, R.J. (2006). Adding interpersonal learning and tacit knowledge to March's exploration-exploitation model. *Academy of management journal*, 49(4), 709-722.

[12] Nonaka, I. and Takeuchi, H. (1995). The knowledge-creating company: how japanese companies create the dynamics of innovation. Oxford university press.

[13] Paoli, M. and Prencipe, A. (2003). Memory of the organisation and memories within the organisation. *Journal of management andgovernance*, 7(2), 145-162.

[14] Schilling, M. A. and Fang, C. (2014). When hubs forget, lie, and play favorites: interpersonal network structure, information distortion, and organizational learning. *Strategic management journal*, 35, 974-994.

[15] Sturm, T., Gerlach, J. P., Pumplun, L., Mesbah, N., Peters, F., Tauchert, C., Nan, N., and Buxmann, P. (2021). Coordinating human and machine learning for effective organizational learning. MIS Quarterly, 45(3), 1581-1602.

[16] Xiao, Y., Cen, J., and Soberg, P. (2021). The impact of disruption on the relationship between exploitation, exploration, and organizational adaptation. *Frontiers in sociology*, (6).

[17] Zhao, C. and Gao, Z. (2014). Who knows what and who is reliable: transactive memory system in multiactivity task environment. *Advances in intelligent systems and computing*, 280, 131-144.