RELATIVE TRANSACTIVE MEMORY ESTIMATION: DEVELOPMENT AND TEST OF AN ECOLOGICALLY VALID FRAMEWORK

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ABSTRACT

In this research we define a new construct, Relative Transactive Memory (RTM) which reflects ebbs and flows in Transactive Memory Systems (TMS). We develop and test a theoretical framework for understanding the association between intra-collective Relative Transactive Memory and objective collective performance over time. Further, given established ecological limitations in the operationalization of TMS, our frame leverages information derived directly from organizational event logs. We test empirical relationships between Relative Transactive Memory, and collective reactivity to change and collectives' capacity to focus on several discrete tasks contemporaneously. We conclude with a discussion of the theoretical and managerial implications of Relative Transactive Memory as an indicator of collective fitness.

Keywords: transactive memory systems (TMS), relative transactive memory (RTM), event logs, ecological validity, longitudinal field test

As competitive intensity (Ang, 2008) and dynamism (Simerly & Li, 2000) continue to rise, organizations have come to rely on teams and other collectives as a vehicle to generate nuanced responses to these obstacles and maintain competitive advantage (Kozlowski & Bell, 2003; Salas, Stagl, & Burke, 2004). Because of the central role collectives increasingly play, it is critical that organizations maintain an accurate, real-time understanding of their relative levels of fitness (Ruef, 1997), or capacity to adapt and respond to change. However, it is difficult, if not impossible to establish useful diagnostic clarity through conventional end-of-quarter performance evaluations or occasional pulse-taking subjective survey assessments that can at best offer only snap-shot illustrations of collective fitness.

In an effort to provide insight into fluctuations in collectives' capacity to perform over time, we develop and test an ecologically valid, longitudinal framework for the evaluation of collective fitness that is derived from transactive memory systems (TMS) theory (Moreland, 1999; Moreland, Argote, &Krishnan, 1996). TMS is a shared cognitive directory that facilitates cooperative information encoding, storage, and division of expertise (Austin, 2003; Ellis, 2006; Lewis & Herndon, 2011; Zhang, Hempel, Han, & Tjosvold, 2007). TMS enables efficient allocation, retrieval and application of scarce personal and collective knowledge resources (Faraj & Sproull, 2000). TMS can also help collectives retain and apply more task-critical knowledge, coordinate their interactions, and perform more effectively than collectives without a TMS (Austin, 2003; Lee, Bachrach, & Lewis, 2014; Lewis, 2003, 2004; Liang, Moreland, & Argote, 1995; Moreland, Argote, & Krishnan, 1996; Moreland & Myaskovsky, 2000; Zhang, Hempel, Han, & Tjosvold, 2007).

However, despite its promise the TMS literature has adopted an exclusively static frame of reference for understanding derivative collective performance consequences. Missing has been theory or research addressing variation in transactive memory over time, or evaluation of collective performance consequences associated with transactive memory ebbs and flows. We refer to these ebbs and flows as relative transactive memory (RTM). Relative Transactive Memory is defined as intra-collective gains and losses in transactive memory over a period of time. Although fostering and effectively managing knowledge is critical to collective performance (Argote & Miron-Spektor, 2011; Winter & Szulanski, 2001), little insight is currently available into the performance consequences of variation in this process over time.

Further, measurement of TMS has emerged as a substantive conceptual issue in the domain. TMS has been operationalized using a range of both indirect and direct measures (e.g., Lewis, 2003; Lin, Hsu, Cheng, & Wu, 2012; Maynard, Mathieu, Rapp, & Gilson, 2012; Moreland & Myaskovsky, 2000). As Ren & Argote (2011) noted, “In spite of general convergence in defining the concept of transactive memory systems, we observed significant divergence in measuring the concept. We identified five [different] sets of [indirect or scale based] established measures of transactive memory systems in the literature.” (2011, p. 212).

In this research, we address two issues specifically. First, with our introduction of the concept of Relative Transactive Memory, we seek to expand the TMS theoretical frame by developing and testing theory bearing on the collective performance consequences of TMS variation over time. Without an explicit emphasis on change, theory building in the area is constrained to a static focus. Second, in light of: 1) substantive variation in how TMS has been operationalized (Ren & Argote, 2011), and 2) inherent structural limitations associated with static snapshots of TMS (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Staw, 1975), we also approach measurement of variation in TMS over time in an ecologically valid way.

We operationalize RTM using an algorithm based on evidence derived directly from embedded organizational event logs (Gaaloul, Bhiri, & Godart, 2004). Because RTM is derived solely from indigenous information contained within event logs, with the algorithm we develop

RTM data is both easy to gather and managerially isomorphic. We propose that because: 1) collectives with greater TMS stability over time are likely to exhibit more functionally responsive reactivity to environmental change, and 2) these collective are likely to have the capacity to focus on more event instances contemporaneously, relative transactive memory (RTM) is a critical indicator of collective performance capacity over time.

BACKGROUND AND THEORETICAL DEVELOPMENT

Transactive Memory Systems

We apply a transactive memory systems frame to contextualize our model. A great deal of effort has been devoted to understanding how intra-collective knowledge and resources are pooled and shared (Austin, 2003; Hollingshead, 1998, 2001; Lewis, 2003). Knowledge management is a process whereby “distributed group members and their organizational colleagues locate, store, and retrieve the data, information and knowledge that they need for their individual and collective work.” (Hollingshead, Fulk, & Monge, 2002: 335). ‘Meta-knowledge’ or socially shared cognition (Moreland, Argote, & Krishnan, 1996) facilitates understanding of members’ knowledge and expertise and enables other members to identify whose knowledge is most relevant across performance contexts.

TMS emerges when members develop insight into what other members know and know how to do. This can happen from members’ own perceptions or expectations (Hollingshead and Fraidin 2003), or often through task-related communications. This shared understanding or meta-knowledge facilitates the location and retrieval of information that over time contributes to a division of cognitive labor where group members assume responsibility for learning, remembering, and communicating information in distinct domains. Thus, TMS contributes to the emergence of efficiencies that are made possible by non-redundant information storage and retrieval and collective memory of the location of information (Lewis & Herndon 2011).

Transactive Memory Systems are undergirded by three principle attributes. The first is differentiated expertise across members, which reflects the extent that members maintain specialized knowledge of distinct, complimentary features of collective responsibilities (Lewis, 2003). The second, mutual reliance, is the degree that individual members rely on others' for their domain-specific knowledge. The third is the extent that members' differentiated expertise can be coordinated as collectives carry out their responsibilities (Lewis, 2003). These attributes of TMS facilitate efficient information search and help to cut down on the loss of task-critical information as this can be transparently assigned in the most applicable member. The maintenance of discrete expertise domains also increases the cumulative knowledge available to collectives and can enhance collective performance (Austin, 2003; Lee, et al., 2014; Lewis, 2003, 2004; Liang, et al., 1995; Moreland, et al., 1996, 2000; Zhang, et al., 2007).

TMS Stability Over Time

For TMS to function, two critical underlying mechanisms must be in operation: member knowledge acquisition in conjunction with timely and efficient inter-member information distribution and transmission (Løwendahl, Revang, & Fosstenløkken, 2001). Knowledge acquisition reflects collective dependence on new, specialized knowledge to deepen members' capacity to function transactively. Knowledge distribution and transmission promote information gathering efficiency, storage and retrieval by facilitating members' access to a large volume of task-relevant information without members having to possess this task-critical information themselves (Wegner, 1987).

As a collective phenomenon TMS depends on the division of labor in both individual (e.g., what individuals know) and collective memory (e.g., how effectively members locate and retrieve others' knowledge - Wegner, 1987). While collective memory provides a structural framework for integrating and distributing collective expertise and knowledge, the value of this architecture depends on continual updating of individual knowledge repositories. Although TMS requires “encoding, storing, and retrieving information” (Ren & Argote, 2011: 191), little is known about how this infrastructure is adapted to emergent environmental constraints or the consequences in changes in this infrastructure over time. Current, up-to-date knowledge repositories facilitate the maintenance of encoding routines that enable efficient knowledge exchanges that coincide with contemporary external demands.

Thus, while TMS can enhance strategic routines (Argote & Ren, 2012), facilitate management of uncertain knowledge demands (Lewis, 2004), and improve collective performance (Ren & Argote, 2011), the system depends on an ongoing balance of members’ individual knowledge and collective awareness both of the location of this knowledge within the system and capacity to use it efficiently. Instability in the processes and structures that undergird transactive memory systems over time represent a functional disruption in the coherence of the meta-cognition critical to TMS functioning.

Instability can upset the functionality of TMS in three principle ways. First, TMS functionality depends on differentiated expertise across members, which reflects the extent that members maintain specialized knowledge of distinct, complimentary features of collective responsibilities (Lewis, 2003). When instability is present in the processes and structures that undergird the TMS, members’ awareness of the domains maintained by other members and their judgment of the appropriate boundaries of their own domain responsibilities can begin to degrade. In the presence of breaks in the transactive process, members are more likely to be unsure of where the most current knowledge/information in a particular area can be located. They also are likely to have uncertainty as to the extent of their own on-going responsibility for maintaining expertise in a particular area. This uncertainty has several potential consequences.

When values of TMS fluctuate, members capacity to consistently establish to whom to go to seek the most current knowledge/information in a particular area is uncertain. What also is uncertain is the extent that inforrmation conduits/expert sources that had been available at previous levels are available at any given point in time, at the level or depth at which they were previously available. In light of dynamism in TMS, members actions, based on past levels of TMS are likely to be inconsistent with current levels within the collective. When TMS fluctuates, members also may not have the most current knowledge/information available to provide to other members who seek it from them – if, for example, TMS decreases. In addition, members also may be more likely to expend time/energy deepening their expertise in domains that are overlapping with those of other members – i.e., if, for example, TMS increases. These consequences diminish the potential value of TMS. In constrast, stability in TMS facilitates consistency in knowledge/information acquisition and distribution patterns.

Second, TMS functionality also hinges on mutual reliance, which is the degree that individual members depend on others' for their domain-specific knowledge. When instability is present in the processes/structures that undergird transactive memory, members are likely to be uncertain of the extent that other members can or will faithfully assume the role of expert they'd been relied on to play. The mutual dependence that is a hallmark of TMS develops over time and through repeated successful interactions and information exchanges. It depends on feelings of trust and confidence. Instability in the TMS can signal that these foundational expectations may be misplaced or unwarranted. If levels of TMS decline, members may be less likely to seek expertise from other members and may, instead, rely on their own (more limited) expertise. If levels of TMS increase, members may inadvertantly underutilize expetise otherwise available from other member experts positioned to provide them with expert insight. Stability in TMS fosters consistency in the level(s) of expertise maintained – and leveraged – by members of the collective.

Finally, TMS functionality depends on the extent that members' collective differentiated expertise is coordinated as collectives complete tasks and responsibilities. When instability is present in the TMS, the on-going tacit communications and interactions that are necessary for coordination of knowledge/expertise can be disrupted. From the distribution side of the equation, members' awareness of who is most likely to need their expertise, how this expertise can be most effectively packaged and transmitted, and in what sequence it is likely to be most useful can become clouded. This can negatively impact the efficiency of the outward flow of relevant information from an expert to other members throughout the collective in need of their expertise. From the application side of the equation, members are less likely to receive knowledge/information from the correct expert, this knowledge/information is less likely to be configured in the most useful way, and it also is less likely to be received in the most coherent sequence. This also can negatively impact the on-going value or utility of the knowledge/information that members receive from experts as they do complete their tasks. Thus, because instability in the processes and structures that define transactive memory systems can negatively impact members' differentiated expertise, mutual reliance, and knowledge/expertise coordination, we propose the following:

> *Hypothesis 1:The stability of Relative Transactive Memory diminishes when the structure of collectives changes (i.e., membership changes).*
>
> *Hypothesis 2: The stability of Relative Transactive Memory is positively associated with collectives' reactivity (i.e., inversely as the time required by a collective to adapt to new process instances).*
>
> *Hypothesis 3:The stability of Relative Transactive Memory is positively associated with collectives' performance.*

METHOD

Sample, Partecipants, Procedure

In order to test the validity of the conceptual framework we propose, we leverage the BPI Challenge 2012 event log as an archetypal event log. This publically available event log[1] encompasses events bearing on the application process for a personal loan or overdraft in a global financing organization. It is important here to note that there are few freely publically available (e.g., publishable) event logs. From this event log, we are able to extract a social network using the Working Together (WT) metric. From this social network we apply a clustering algorithm to discover definable collectives within the organization. The clustering algorithm we adopt for this purpose is the stabilized Label Propagation algorithm (see Xie & Szymanski, 2013).

Analytical approach

The principle assumption underlying our approach is that the development of a function within a specific time interval [0,1] enables us to return the value of the Transactive Memory within a collective at a given point in time. Because of the nature of the context within which the framework is evaluated, this function generates a value that is comparable within a collective over time. Given two instants in time, t_1 and t_2, the function allows us to establish when Transactive Memory is higher in the collective. We don't set target values of TMS to be comparable across different collectives, because too many variables are present. This is the reason we refer to the focal predictive variable in our model as Relative Transactive Memory.

In order to be ecologically coherent, the measure of RTM has to account for activities encompassed by the event log, and the employees in the collective for which we seek to calculate the relative transactive metric. Consistent with approaches reported in the literature (e.g., Chen,

[1] On http://www.win.tue.nl/bpi/2012/challenge

Li, Clark, & Dietrich, 2013; Ellis, 2006; Robertson, Gockel, & Brauner, 2013) we propose to estimate transactive memory gains and losses through evaluation of dynamism in the following two elements of transactive memory:

1. **Specialization**: when the collective has greater Transactive Memory, workers are specialized and have a defined core set of task-critical knowledge and information.

2. **Coordination:** when the collective has greater Transactive Memory, workers are coordinated through a stable work flow, and there is a more systematic transaction of tasks.

These characteristics can be measured through two quantities that we refer to as the Average Prevalence of Actions (APA) and the Average Prevalence of Handovers (APH). These quantities provide a value (for the characteristic) in a given number of subintervals of the macro time interval in focus. We define RTM operationally as the average of APA and APH. We first account for both specialization and coordination. We then explain how to find an optimal number of subintervals in the time interval.

Event Logs and Social Networks

The efficient transmission and application of information and knowledge within collectives is essential for the maintenance of competitive advantage (Teece, Pisano, & Shuen, 1997). The structure of the relationships between individuals embedded within collectives has a direct impact on their access to crucial knowledge (Baldwin, Bedell, & Johnson, 1997; Cross & Sproull, 2004; Klein, Lim, Saltz, & Mayer, 2004). The connections afforded by social relationships provide a foundation for “social capital” which has been defined as the sum of the actual and potential resources embedded within, available through, and derived from ties within networks of social relationships (Bourdieu, 1986; Burt 1992).

In organization contexts (Van der Aalst, 2005) an understanding of the structure of extant social networks may be built based on evidence derived from event logs (Van der Aalst, et al., 2004; van Donegen, et al., 2005). Event logs are formal collections of information reflecting on relationships between events happening in an organization. Information in event logs includes:

- An event's timestamp, which we refer to in this research as $\varrho_t(e)$ where e is the event.
- A process instance (which can also be called a case) in which an event is deployed, which in this research we refer to as $\varrho_c(e)$ where e is the event).
- An event's originator (which is the specific employee who executes the event). In this research we refer the originator as $\varrho_w(e)$ where e is the event.

Consistent with the approach reported by Carrington, Scott, and Wasserman (2005) we conceptualize a social network as a weighted graph $G=(V,E)$, where:

- nodes represent individuals (workers), and are identified by integers. Thus V, the set of nodes, is a subset of the set of natural numbers;
- edges represent relations between workers, and are identified by couples $e=(i,j)$ (where i and j are identifiers of nodes). The set of edges E is a subset of $V\times V$;
- weights are associated with each of the edges.These weights represent the *strength* of the relationship represented by the corresponding edge. Mathematically, they can be understood as functions from E to R. Given an edge $(i,j)\in E$ the associated weight is denoted as $w((i,j))\in R$.

To effectively build the social network, weights between 0 and 1 are assigned to relations among individuals. This can be done by calculating a metric between individuals. In Van der Aalst et al. (2005), several metrics have been proposed, including the following:

- The Handover of Work (HoW) metric captures how many times the work of an individual for a process instance is followed by the work of another individual.
- The Working Together (WT) metric captures how many times two individuals work together in any given process instance.

In this research, because we build our framework on a transactive memory systems theory scaffold (Wegner, 1987; Wegner, Erber, & Raymond, 1991) we focus primarily on the Working Together (WT) metric between two individuals p_1 and p_2. WT(p_1,p_2) is the ratio of the number of instances in which both p_1 and p_2 execute an event, and the number of instances contained in the log in which p_1 executes events. The value of the metric is higher when individuals often collaborate.

Once a social network has been defined, information can be mined from it, for example, through the use of a clustering algorithm. A clustering algorithm groups individuals based on similarities in their work-related activity profile, to extract information about the structure of the relationships between employees in an organization (Newman & Girvan, 2004; Palla, Derényi, Farkas, & Vicsek, 2005; Lancichinetti, Fortunato, & Kertz, 2009). A clustering *C* of *G* is a family of subsets of *V* such that each node is assigned to exactly one cluster. We can define a function $C{:}V \rightarrow N$ where $C(v)=i \Leftrightarrow v \in S_i$ (*v* belongs to the cluster S_i). Although multiple clustering algorithms have been published in the literature, (e.g., Blondel, Guillaume, Lambiotte, & Lefebvre, 2008; Raghavan, Albert, & Kumara, 2007; Geyer-Schulz, 2012; Liu, Kang, An, & Zhou, 2014; Ng, Jordan, & Weiss, 2001; Malliaros & Vazirgiannis, 2013; Palla et al. , 2005), unfortunately the majority of these work on undirected graphs.

So, in order to use these algorithms on a directed graph, the graph would have to be transformed from a directed graph into an undirected graph (i.e. constraining edges (i,j) and (j,i) to have the same weight). Although with this transformation information about directionality is lost, this does not necessarily lead to the loss of information about relationships in the social network (for discussion, see Malliaros & Vazirgiannis, 2013).

The availability of an event log, however, facilitates the generation of more (and richer) information than patterns of relationships contained in social networks extracted from activity metrics. With an event log, full insight is available into business processes, and it is possible to do a business process improvement (BPI) analysis (van Dongen et al., 2005). A potentially interesting analysis might, for example, incorporate instances of completion times. Instances with higher duration are indicative of poorer performance (for example, breaking Service Level Agreements); while instances with lower duration can serve as a positive performance signal.

The concept of low duration instances, which in Lean Manufacturing terminology (Staats, Brunner, & Upton, 2011; Stratton & Warburton, 2003) is referred to Lead Time, is the latency or delay between the initiation and execution of an event (Parasuraman & Alutto, 1984). Indeed, with a focus on a process, it is possible to calculate the average (*avg*) completion time of instances, and the standard deviation (*std*) of completion times. Fixing a constant k (e,.g., k=1) to the equation, we can define "Positive" instances as having a duration below $avg - k \cdot std$; "Normal" instances as having duration between $avg - k \cdot std$ and $avg + k \cdot std$.; and "Negative" instances as having a duration in excess of Lead Time, above $avg + k \cdot std$.

Measures

Collective workload. We define collective workload in a given sub-(time) interval as the number of process instances achieved by the collective in the sub-interval.

Collective performance. Collective performance is operationalized as the ratio between the percentage of process instances executed by the collective exceeding Lead Time, which is set to be $avg + k \cdot std$ with k=1.5, and the collective's workload. Although other values for k are possible (e.g., k=1.0, k=3.0, k=6.0), our (compromise) choice for the value of k in the log is k=1.5. We make this choice because, with a value of k=1.0, almost 40% of process instances in the log would exceed this threshold, while with a value of k=2.0 less than 10% of process instances would exceed this threshold. However, with k=1.5 approximately 15% of process instances would exceed this threshold.

Average Prevalence of Action. We introduce a measure, APA or Average Prevalence of Action. APA is high when a worker is specialized in the execution of a particular task. Being a temporal measure, a value for each sub-interval has to be set. Being a relative measure, we have defined APA as varying from 0 to 1. A value of 0 is assumed when prevalence is at its lowest level. A value of 1 is assumed when prevalence is at its highest level. The logic underlying APA is that each worker can do several things within a particular time subinterval.

However, there can be one (or more than one) particular type of activity that is most prevalent, considering the number of times it is accomplished within a particular time frame. This measure is built in two steps. First we build the average prevalence of actions among workers in the sub-intervals (APA_Prel). Second, we normalize the results obtained in the previous point in time (APA). APA_Prel, for a given time interval, accounts for the percentage of events executed for the prevalent action and computes the average.

For example, assume the collective has two workers, A and B. During a specific time interval, Worker A executes Activity1 in 60% of events and Activity2 in 40% of events. WorkerB executes Activity1 in 45% of events and Activity2 in 55% of events. With these distributions, APA_Prel for the focal interval is equal to (0.6+0.55)/2=0.575. This approach is implemented in Algorithm 1, which is used to calculate APA_Prel for each subinterval and can be found in Appendix 1.

Building from the value of APA_Prel for each sub-interval, APA is simply the normalization of the value. It assigns a value of ‘0’ to the sub-interval with the least APA_Prel, it assigns a value of ‘1’ to the sub-interval with the highest value of APA_Prel, and an intermediate value in all other cases. The method implemented in Algorithm 2, which is used to calculate APA for each subinterval, can also be seen in the Appendix.

Average Prevelance of Handover. We introduce a second measure, Averrage Prevalance of Handover or APH, which is a defined quantity for each sub-interval that measures collective coordination. The measure accounts for each instance executed by members of the collective, the numberr of handovers between different members of the collective, and the number of events in the instance that were executed by members of the collective.

We then propose two algorithms. The first (APH_Prel, see Algorithm 3 in the Appendix) calculates the ratio between the number of handovers made inside the collective and the number of events. For example, consider a time interval where there is only one instance worked. If that instance consists of events executed respectively by User A, User A, and User B, then the number of events is 3, the number of handovers between different members of the collective is 1, and the APH_Prel value for the interval is $^1/_3$ or 0.33. The APH algorithm (Algorithm 4 can be found in the Appendix) accomplishes normalization of the value. This is the algorithm used to calculate APH for each subinterval. Again, our goal here is to define a measure that is relative. It's range extends from 0 to 1. This value is higher when there are a lower number of handovers, and transactive memory is higher.

Evaluating Relative Transactive Memory

After defining measures of APA and APH that are built from input directly from the event log, the collective in focus, and the number of temporal subintervals, RTM for a given number of subintervals can be determined by averaging APA and APH. This measure, depicted in Algorithm 5 (in the Appendix), accounts for both specialization and coordination. A crucial conceptual issue is the determination of an optimal number of subintervals, in order to maximize information that RTM can provide (i.e. a precise localization of the points in time in which RTM is higher, or in which it declines).

Our approach emerges from the recognition that there is a strong, negative correlation between RTM and the number of instances executed by members of the collective in each of the temporal subintervals. Working new instances requires the collective to reorganize to a certain extent. As a consequence there is a shift in levels of Transactive Memory present in the collective. Given a specified number of sub-intervals, it is possible to determine the number of new instances worked by the group for each sub-interval using Algorithm 6 (as can be seen in the Appendix). The approach described in Algorithm 7 (also in the Appendix) is then used to try every possible number of temporal sub-intervals in order to maximize the negative correlation between RTM and the number of new instances occurring in each sub-interval. We approach the search from a minimum to a maximum number of intervals, depending on the length of the time interval. For example, if the interval is 1 year, we can search between 12 intervals (e.g., the sub-interval is equivalent to a month) and 365 (e.g., each day is a discrete sub-interval).

Evaluating Stability

Relative Transactive Memory is reflected in the extent that substantive variations in RTM across focal time intervals are absent (e.g., RTM is broadly stable). This is a function of variance. In Algorithm 8 we propose to use the inverse of the variance as a measure of the Stability of RTM. Algorithm 8 can be found in the Appendix.

Evaluating Reactivity

Finally, we define *reactivity* as the time required by a collective to adapt to changes in the organization or to new process instances in the event log. Our expectation is that we will uncover a significant negative assocation between values of RTM and the number of new process instances executed during the focal time intervals.

Given an array of RTM values, the method to evaluate reactivity accounts for the average (time) distance between a local minimum and the next local maximum. This value is calculated using Algorithm 9 (in the Appendix). A local minimum is a sub-interval in which RTM is lower than its neighboring sub-intervals (i.e. the value of RTM immediately prior to and the value of RTM immediately subsequent to the focal value). A local maximum is a sub-interval in which RTM is higher than its neighbouring sub-intervals.

For example, if we consider 4 sub-intervals: A) in which RTM is 0.4, B) In which RTM is 0.3, C) in which RTM is 0.5, and D) in which RTM is 0.2, then sub-interval B is a local minimum (as $0.3 < 0.4$ and $0.3 < 0.5$), while C is a local maximum (as $0.5 > 0.3$ and $0.5 > 0.2$). It is critical to note here that, theoretically, there is a chance of neighboring values being equal. However, the probability of observing these equivalent values in a real event log (e.g., such as the BPI Challenge 2012 event log) is extremely low. Here, all of the values of RTM in the sub-intervals for the BPI Challenge 2012 event log were discrete.

The distance is then calculated as the ratio between the difference of position between the local maximum, local minimum and the total number of subintervals. In the example above, C is local maximum and is the 3rd subinterval, B is local minimum and is the 2nd subinterval. Because the difference is 1 and the total number of subintervals is four, the ratio is ¼ = 0.25. Algorithm 9 takes into account all the distances between local maxima and local minima which are their predecessors, computes the average (which is a number between 0 and 1) and then the multiplicative inverse. The obtained quantity is high when local maxima are near to local minima, indicating high reactivity to change in the collective.

RESULTS

Preliminary analysis

In the BPI Challenge 2012 event log there are two collectives with >3 workers. We refer to these collectives as Group 1 and Group 2. Group 1 contains workers identified in the Event Log by the numbers 10861, 11180, 10982, 11254. Group 2 contains workers identified in the Event Log by the numbers 10138, 11179, 11269, 10125.

For these two groups, we calculated RTM. We did this using Algorithms 5, 6, and 7 in order to determine the number of subintervals that maximizes the negative correlation between RTM and the number of new instances in each subinterval that were worked by members of each of the two groups. A depiction of RTM for both Group 1 and Group 2 is presented in Figures 1a

& 1b. As can be seen from Figure 1a, for Group 1, the number of subintervals maximally negatively correlated with new instances in each subinterval is 71. The correlation between RTM and the number of new instances is −0.716. As can also be seen in Figure 1b, for Group 2, the number of subintervals maximally negatively correlated with new instances in each subinterval is 56. The correlation between RTM and the number of new instances is −0.216.

Insert Figures 1a & 1b about Here

Applying Algorithm 8, the results from our analysis reveal that Group 1 has a level of stability of 76.34, while Group 2 has a level of stability 51.55. These results indicate that the Relative Transactive Memory in the first group is more stable than in the second group.

Hypothesis Tests

In Hypothesis 1, we predict that the stability of RTM diminishes when the structure of the collective changes. As is made clear in Figure 1a, we see a strong, negative correlation in Group 1 between RTM and the number of new instances executed by members of the group. In constrast, what Figure 1b also makes clear is that the correlation between RTM and the number of new instances in Group 2 is substantially lower. This coincides with a change in the internal dynamics of the groups precipitated by the absence of worker 11179. Indeed, as can be seen in Figure 2, there are two substantial declines in RTM. The first is positioned between 0.15 and 0.25, and the second in the vicinity of 0.3.

As can also be seen in Figure 2, worker 11179 disappears from the event log at the point of the first decline in RTM, and returns at the point in time coinciding with the second decline. This pattern is consistent with evidence from the literature (e.g., Peltokorpi, 2008) that TMS declines when group composition changes. Thus, RTM appears to retain this attribute of TMS.

In constrast, as can be seen in the Figure 1b, there are no absences, and no sudden decreases in RTM. This pattern of results provides support for the prediction made in Hypothesis 1.

Insert Figure 2 about Here

In Hypothesis 2, we predict that stability of Relative Transactive Memory is positively associated with collectives' reactivity (e.g., the time required by a collective to adapt to changes to new process instances). As can be seen in Figure 1a, Group 1 is both more stable and more reactive. The RTM stability in Group 1 is 76.34, while the reactivity of the group is 43.29. In contrast, the RTM stability of Group 2 is 51.55 while its Reactivity is 33.56. This pattern of results suggests that more stable RTM is positively associated with reactivity.

As can be seen comparing Figures 1a and 1b, at least for the two groups we evaluated, higher RTM stability is related to better reactivity. Applying the same algorithms reported above to the private event log of an organizational process that counts 221 workers, and in which there are several different collectives (e.g., the stabilized Label Propagation algorithm generated 38 discrete clusters), we can see that this trend is consistent with the pattern of results presented in Table 1. These results provide additional support for Hypothesis 2.

Insert Table 1 about Here

Finally, in Hypothesis 3 we predict that the stability of RTM is positively associated with collectives' performance. As can be seen in Figure 3, while Group 1 has a greater workload, it also has an approximately equivalent percentage of process instances exceeding Lead Time (which we have set to be $avg+k\cdot std$, with k=1.5). This can be seen comparing Figures 1a and 1b. From this pattern of results, we conclude that RTM stability is positively related to stronger collective performance. Collectives with more stable RTM are more capable of efficiently coping with a higher workload. This pattern of results provides support for Hypothesis 3.

Insert Figure 3 about Here

DISCUSSION

In this research we focus on longitudinal dynamism in TMS. We also introduce the concept of Relative Transactive Memory. Building directly from transative memory systems theory (Wegner, 1987; Wegner, et al., 1991), and empirical evidence from the literature (e.g., Peltokorpi, 2008), we find that the stability of RTM diminishes when the structure of the collective in which it is evaluated changes. This pattern of results points to the core role played by the social context within which TMS can emerge for understanding ebbs and flows in Transactive Memory Systems over time.

In this research we also explore the capacity of collectives to respond to environmental change. We find that the stability of intra-collective RTM is associated with collectives' reactivity; or inversely as the time to adapt to changes to new process instances. These results provide support for Hypothesis 2, and from foundational theory in the domain (Lewis & Herndon, 2011) speak to the importance of consistency in collectives' knowledge infrastructure and meta-knowledge for responding to environmental dynamism (Simerly & Li, 2000). Finally, critical to the utility of the approach we describe, in support of Hypothesis 3 we also find that collectives with more stable RTM are capable of efficiently coping with higher workloads than collectives with less stable Relative Transactive Memory. This suggests that RTM can be a critical indicator of collectives' fitness - or capacity to perform - over time (Ruef, 1997).

Theoretical Implications

Our principal goal in this research was to introduce an element of dynamism into the theoretical infrastructure informing research and theory building in the TMS area. The framework we report suggests that there may be utility in conceptualizing TMS as an inherently dynamic infrastructure. A transactive memory system can emerge in collectives when members develop insight into what others know and what they are able to do. This awareness can derive from explicit information such as past performance records (Moreland & Myaskovsky 2000), from subjective perceptions or expectations (Hollingshead & Fraidin 2003), or through task-related communication. This shared understanding is crucial for the development of a TMS (Moreland, 1999; Moreland et al. 1996, 1998; Wegner 1987).

However, rather than emerging – and remaining – at a constant or near constant level, what is clear is that the processes and structures reflective of TMS (Lewis, 2003) can and do vary intra-collectively over time. Further, these variations also appear to have substantive implications for both how well collectives are capable of responding to enviromental change and also how well these collectives are able to perform. In light of this variation, it will be important for future research and theory-building to continue to focus on the dynanism inherent within TMS to more fully articulate the nature of these ebbs and flows. Understanding how TMS changes, and perhaps more importantly why it changes over time, will be a critical next step.

Practical Implications

There are inherent basic architectural limitations associated with evaluating complex intra-collective structures and processs, using either direct or indirect approaches (e.g., Ren & Argote, 2011), at a single point in time (Lindell & Whitney, 2001; Podaskoff et al., 2003). The snapshot of action captured using a single survey, or observational event (e.g., Ellis, 2006; Moreland & Myaskovsky, 2000) is definitionally static and as a consequence doesn't allow for the development of inferences bearing on change over time. Moreover, managers provided with evidence of TMS at a single point can't know whether this value is trending upward or downward. As a consequence, managers can derive no diagnostic clarity as to the relative fitness of the collective for which they are responsible, whether to either arrest a negative trend or support a positive trend, or how to support the group.

Further, functionally intrusive data collection events also can *ipso facto* substantively impact the focal processes under observation. Through the mere fact of measurement itself (Dholakia & Morwitz, 2002; Morwitz & Fitzsimons, 2004) the picture managers are able to generate as to the condition of their work group can be biased. What we propose is a straightforward, ecologically valid, non-intrusive, longitudinal method that can in real-time provide practicing managers with embedded insight into the relative fitness of the collectives they lead. Because this approach is based on indigenous organizational data, it can be used to define and orchestrate meaningful, substantive collective peformance interventions.

Study Limitations

Of course, as with all empirical research, the conclusions we are able to draw - and the applicability of the approach we define – is constrained by limitations of the design of our study. While the use of event logs carries with it the substantial benefits described above, this is also a limitation in the possibile application of RTM as a diagnoistic vehicle. The reality is that only a relatively small (and only slowly increasing) number of organizations have established a level of process awareness such that they record events automatically in event logs; or use them either for business analysis and for business process intelligence. Moreover, there are only few freely available event logs (one of them being the BPI Challenge 2012 log used in this research).

A second limitation in the use of event logs is that we can't know more than what is actually incuded in the log. So, although we may discover functionally meaningful groups through the use of a clustering algorithm, we can't develop inferences bearing on other potentially critical collective performance variables such as levels of cohesiveness (e.g., Mullen & Cooper, 1994), social identity (e.g., Ashforth & Mael, 1989) or psychological safety (e.g., Edmondson, 1999). What we also can't develop inferences about through the use of event logs is the ways in which the members of focal collectives actually share task-critical knowledge and information. Thus, while estimation of the levels of intra-collective TMS through the use of the RTM approach we describe appears to provide a functional working model, it clearly will require additional development for its full potential to be realized.

Conclusions

In this research, we approach the evaluation of collective fitness through a transactive memory systems lens. Moreover, we also address the collective performance implications of dynamism in the processes and structures that undergird TMS. We adopt a novel avenue to evaluate transactive memory that has substantive managerial applicability. We find that intra-collective transactive memory systems can be dynamic. We also find that the stability of Relative Transactive Memory can have substantive implications for collectives' capacity to both deal with environmental change and to perform effectively. Because of these relationships, it is essential that theory and research in the transactive memory systems area expand current conceptualizations to encompass inherent intra-collective dynamism in TMS.

REFERENCES

Ang, S. H. 2008. Competitive intensity and collaboration: Impact on firm growth across technological environments. ***Strategic Management Journal***, 29: 1057-1075.

Argote, L., & Miron-Spektor, E. 2011. Organizational learning: From experience to knowledge. ***Organization Science***, 22: 1123-1137.

Argote, L., & Ren, Y. 2012. Transactive Memory Systems: Micro Foundations of Dynamic Capabilities. ***Journal of Management Studies*** 49: 1375-1382.

Ashforth, B. E., & Mael, F. 1989. Social identity theory and the organization. ***Academy of Management Review***, 14: 20-39.

Austin, J. R. 2003. Transactive memory in organizational groups: The effects of content, consensus, specialization, and accuracy on group performance. ***Journal of Applied Psychology***, 88: 866-878.

Baldwin, T.T., M.D. Bedell, J.L. Johnson. 1997. The social fabric of a team-based MBA program: Network effects of student satisfaction and performance. ***Academy of Management Journal,*** 40: 1369-1397.

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. 2008. Fast unfolding of communities in large networks. ***Journal of Statistical Mechanics: Theory and Experiment***, P10008

Bourdieu, P. 1986. The forms of capital. J.G. Richardson, ed. ***Handbook for Theory and Research for the Sociology of Education.*** Greenwood, New York.

Burt, R.S. 1992. ***Structural holes: The Social Structure of Competition***. Harvard University Press, Cambridge, MA.

Carrington, P. J., Scott, J., & Wasserman, S. 2005. ***Models and methods in social network analysis.*** plus 0.5em minus 0.4emCambridge university press, vol. 28.

Chen, Z., Li, X, Clark, J. G., & Dietrich, G. B. 2013. Knowledge sharing in open source software project teams: A transactive memory system perspective. ***International Journal of Information Management***, 33: 553-563.

Cross, R., L. Sproull. 2004. More than an answer: Information relationship for actionable knowledge. ***Organization Science*** 15: 446-462.

Dholakia, U. M. & Morwitz, V. G. 2002. The scope and persistence of mere-measurement effects: evidence from a field study of customer satisfaction measurement. ***Journal of Consumer Research***, 29: 159-167.

Edmondson, A. 1999. Psychological safety and learning behavior in work teams. ***Administrative Science Quarterly***, 44: 350-383.

Ellis, A. P. J. 2006. System Breakdown: The role of mental models and transactive memory in the relationship between acute stress and team performance. ***Academy of Management Journal***, 49: 576-589.

Gaaloul, W., Bhiri, S. & Godart, C. 2004. Discovering workflow transactional behavior from event-based log, in ***On the Move to Meaningful Internet Systems***. *CoopIS, DOA, and ODBASE*. plus 0.5em minus 0.4em, pp. 3-22. Springer, NY.

Ovelgonne, M., & Geyer-Schulz, A. 2012. An ensemble learning strategy for graph clustering. ***Graph Partitioning and Graph Clustering***, 588: 1-15.

Hollingshead, A.B. 1998. Retrieval processes in transactive memory systems. ***Journal of Personality and Social Psychology***, 74: 659-671.

Hollingshead, A. B. 1998. Communication, learning, and retrieval in transactive memory systems. ***Journal of Experimental Social Psychology***, 34: 423-442.

Hollingshead, A. B. 2001. Cognitive interdependence and convergent expectations in transactive memory. ***Journal of Personality and Social Psychology***, 81: 1080.

Hollingshead, A.B. & Fraidin, S. N. 2003. Gender stereotypes and assumptions about expertise in transactive memory. ***Journal of Experimental Psychology***, 39: 355-363.

Hollingshead, A. B., Fulk, J., & Monge, P. 2002. Fostering intranet knowledge sharing: An integration of transactive memory and public goods approaches. In P. Hinds, & S. Kiesler (Eds.), ***Working Across Distance***: 335-355. Boston, MA: MIT Press.

Klein, K.J., Lim, B.C., Saltz, J. L., & Mayer, D. M. 2004. How do they get there? An examination of the antecedents of centrality in team networks. ***Academy of Management Journal,*** 47: 952-963.

Kozlowski, S. W., & Bell, B. S. 2003. Work groups and teams in organizations. In W. C. Borman, D. R. Ilgen, & R. J. Klimoski (Eds.), ***Handbook of psychology: Industrial and organizational psychology*** (Vol. 12, pp. 333–375). London: Wiley.

Lancichinetti, A., Fortunato, S., & Kertz, J. 2009. Detecting the overlapping and hierarchical community structure in complex networks. ***New Journal of Physics***, 11, 033015

Lee, J. Y., Bachrach, D. G., & Lewis, K. L. 2014. Social network ties, transactive memory, and performance in groups. ***Organization Science***, 25: 951-967

Lewis, K. 2003. Measuring transactive memory systems in the field: Scale development and validation. ***Journal of Applied Psychology***, 88: 587-604.

Lewis, K. 2004. Knowledge and performance in knowledge-worker teams: A longitudinal study of transactive memory systems. ***Management Science***, 50: 1519-1533.

Lewis, K., & Herndon, B. 2011. Transactive memory systems: Current issues and future research directions. ***Organization Science***, 22: 1254-1265.

Liang, D.W., Moreland, R., & Argote, L. 1995. Group versus individual training and group performance: The mediating role of transactive memory. ***Personality and Social Psychology Bulletin***, 21: 384-393.

Lin, T. C., Hsu, J. S. C., Cheng, K. T., & Wu, S. 2012. Understanding the role of behavioral integration in ISD teams: An extension of transactive memory systems concept. ***Information Systems Journal***, 22: 211-234.

Lindell, M. K., & Whitney, D. J. 2001. Accounting for common method variance in cross-sectional research designs. ***Journal of Applied Psychology***, 86: 114-121.

Liu, S., Kang, Q., An, J., & Zhou, M. 2014. A weight-incorporated similarity-based clustering ensemble method. ***Networking, Sensing and Control (ICNSC)***, *2014 IEEE 11th International Conference on*. plus 0.5em minus 0.4emIEEE, pp. 719–724.

Løwendahl, B. R., Revang, Ø., & Fosstenløkken, S. M. 2001. Knowledge and value creation in professional service firms: A framework for analysis. ***Human Relations***, 54: 911-931.

Malliaros, F.D. & Vazirgiannis, M. 2013. Clustering and community detection in directed networks: A survey. ***Physics Reports***, 533: 95–142.

Maynard, M. T., Mathieu, J. E., Rapp, T. L., & Gilson, L. L. 2012. Something(s) old and something(s) new: Modeling drivers of global virtual team effectiveness. ***Journal of Organizational Behavior***, 33: 342-365.

Moreland, R. L. 1999. Transactive memory: Learning who knows what in work groups and organizations. In L. Thompson, D. Messick, &J. Levine (Eds.), ***Shared cognition in organizations: The management of knowledge***: 3-31. Mahwah, NJ: Erlbaum

Moreland, R. L., Argote, L., & Krishnan, R. 1996. Socially shared cognition at work: Transactive memory and group performance. In J.L. Nye & A.M. Brower (Eds.), ***What's social about social cognition? Research on socially shared cognition in small groups***: 57-84). Thousand Oaks, CA: Sage.

Moreland, R.L., Argote, L., & Krishnan, R. 1998. Training people to work in groups. R.S. Tindale, L. Heath, eds. ***Theory and Research on Small Groups: Social Psychological Applications to Social Issues***. Plenum Press, New York, 37-60.

Moreland, R.L., & Myaskovsky, L. 2000. Exploring the performance benefits of group training: Transactive memory or improved communication? ***Organizational Behavior and Human Decision Processes***, 82: 117-133.

Morwitz, V. G., & Fitzsimons, G. J. 2004. The mere-measurement effect: Why does measuring intentions change actual behavior? ***Journal of Consumer Psychology***, 14: 64-74.

Mullen, B., & Copper, C. 1994. The relation between group cohesiveness and performance: An integration. ***Psychological Bulletin***, 115: 210-227.

Newman, M. E. J., & Girvan, M. 2004. Finding and evaluating community structure in networks. ***Physical Review E***, vol. 69, no. 2.

Ng, A. Y., Jordan, M. I., & Weiss, Y. 2001. On spectral clustering: Analysis and an algorithm. ***Advances in Neural Information Processing Systems***. plus 0.5em minus 0.4emMIT Press, pp. 849–856.

Palla, G., Derényi, I.,. Farkas, I., & Vicsek, T. 2005. Uncovering the overlapping community structure of complex networks in nature and society. ***Nature***, 435: 814–818.

Parasuraman, S., & Alutto, J. A. 1984. Sources and outcomes of stress in organizational settings: Toward the development of a structural model. ***Academy of Management Journal***, 27: 330-350.

Peltokorpi, V. 2008. Transactive memory systems. ***Review of General Psychology,*** 12: 378-394.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. ***Journal of Applied Psychology***, 88: 879-903.

Raghavan, U.N., Albert, R., & Kumara, S. 2007. Near linear time algorithm to detect community structures in large-scale networks. ***Physical Review** E*, 76, 036106

Ren, Y., & Argote, L. 2011. Transactive memory systems 1985-2010: An integrative framework of key dimensions, antecedents, and consequences. ***Academy of Management Annals***, 5: 189-229.

Robertson, R., Gockel, C., & Brauner, E. 2013. Trust your teammates or bosses? Differential effects of trust on transactive memory, job satisfaction, and performance. ***Employee Relations***, 35: 222-242.

Ruef, M. 1997. Assessing organizational fitness on a dynamic landscape: An empirical test of the relative inertia thesis. ***Strategic Management Journal***, 11: 837-853.

Salas, E., Stagl, K. C., & Burke, C. S. 2004. 25 years of team effectiveness in organizations: research themes and emerging needs. ***International Review of Industrial and Organizational Psychology***, 19: 47-92

Simerly, R. L., & Li, M. 2000. Environmental dynamism, capital structure and performance: a theoretical integration and an empirical test. ***Strategic Management Journal***, 21: 31-49.

Staats, B.R., Brunner, D.J., Upton, D.M., 2011. Lean principles, learning, and knowledge work: Evidence from a software services provider. ***Journal of Operations Management*** 29: 376-390

Staw, B. M. 1975. Attribution of the “causes” of performance: A general alternative interpretation of cross-sectional research on organizations. ***Organizational Behavior and Human Performance***, *13*: 414-432.

Stratton, R., Warburton, R.D.H., 2003. The strategic integration of agile and lean supply. ***International Journal of Production Economics*** 85: 183-198

Teece, D.J., G. Pisano, A. Shuen. 1997. Dynamic capabilities and strategic management. ***Strategic Management Journal*** 18**:** 509-533.

Van Der Aalst, W. M., Reijers, H. A., & Song, M. 2005. Discovering social networks from event logs. ***Computer Supported Cooperative Work***, 14: 549–593.

Van der Aalst, W., Weijters, T., & Maruster, L. 2004. Workflow mining: Discovering process models from event logs. ***Knowledge and Data Engineering, IEEE Transactions***, 16: 1128–1142.

van Dongen, B. F., de Medeiros, A.K.A., Verbeek, H., Weijters, A., & Van Der Aalst, W. M. 2005. The prom framework: A new era in process mining tool support. ***Applications and Theory of Petri Nets*** plus 0.5em minus 0.4emSpringer, pp. 444–454.

Wegner, D. M. 1987. Transactive memory: A contemporary analysis of the group mind. In B. Mullen & G. R. Goethals (Eds.), ***Theories of group behavior*** (Vol. 9): 185-208. New York, NY: Springer.

Wegner, D.M., Erber, R., & Raymond, P. 1991. Transactive memory in close relationships. ***Journal of Personality and Social Psychology,*** 61: 923-929.

Winter, S. G., & Szulanski, G. 2001. Replication as strategy. ***Organization Science***, 12: 730-743.

Xie, J. & Szymanski, B. K. 2013. Labelrank: A stabilized label propagation algorithm for community detection in networks. ***Network Science Workshop (NSW),*** *2013 IEEE 2nd*. plus 0.5em minus 0.4emIEEE, pp. 138–143.

Zhang, Z., Hempel, P. S., Han, Y., & Tjosvold, D. 2007. Transactive memory system links work team characteristics and performance**.** ***Journal of Applied Psychology***, 92: 1722-1730.

Group	No. ind.	Stability	Reactivity
1	21	**75.47**	22.56
2	13	**76.51**	**26.10**
3	12	**106.61**	23.20
4	10	35.04	21.75
5	10	18.74	23.20
6	8	23.38	18.45
7	8	62.24	15.62
8	7	23.77	15.62
9	6	**75.26**	19.33
10	6	63.07	19.33
11	6	29.52	17.40
12	6	61.58	21.75
13	6	22.89	17.85
14	6	30.22	20.30

Table 1: Relative Transactive Memory stability and reactivity estimation on a private (larger) event log. Only work groups (based on the Working Together metric and applying the stabilized Label Propagation algorithm for clustering) with >= 6 members are reported. As can be seen in the table, work groups with greater stability also have typically greater reactivity (the correlation between stability and reactivity is $\sigma = .44$).

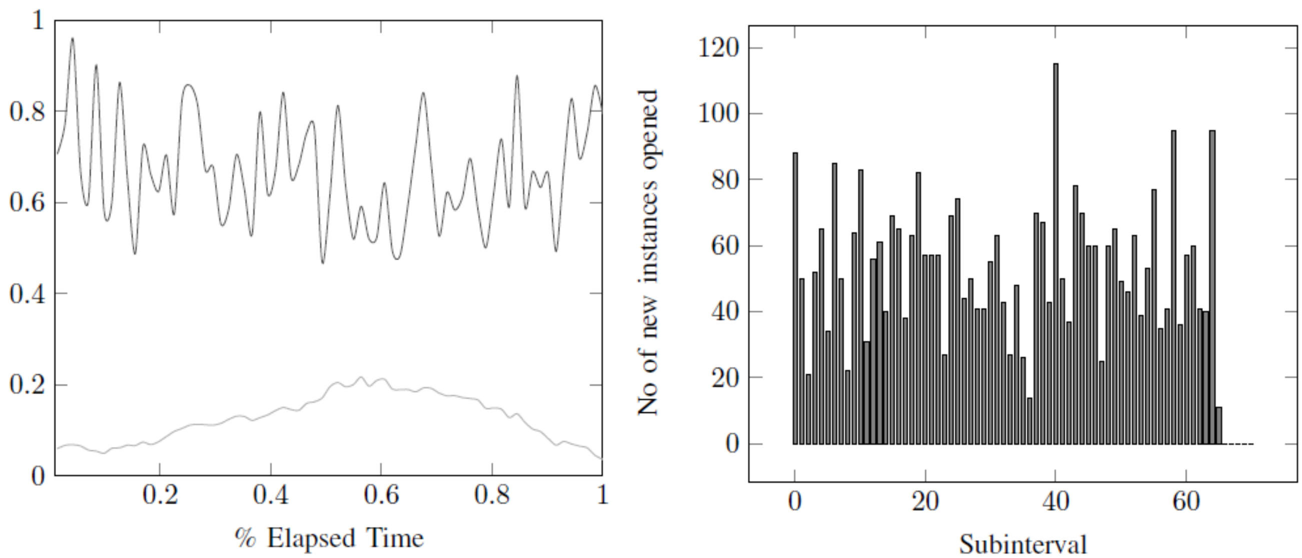

Figure 1a: In the left graph, the darker line is the Relative Transactive Memory for Group 1, for each of the time sub-intervals. The lighter line is the percentage of instances exceeding Lead Time (*avg*+*k*·*std*, with *k*=1.5). The right histogram reflects the number of new instances for each subdivision. As can be seen in the figure, there is a strong high negative correlation between RTM and the number of new instances.

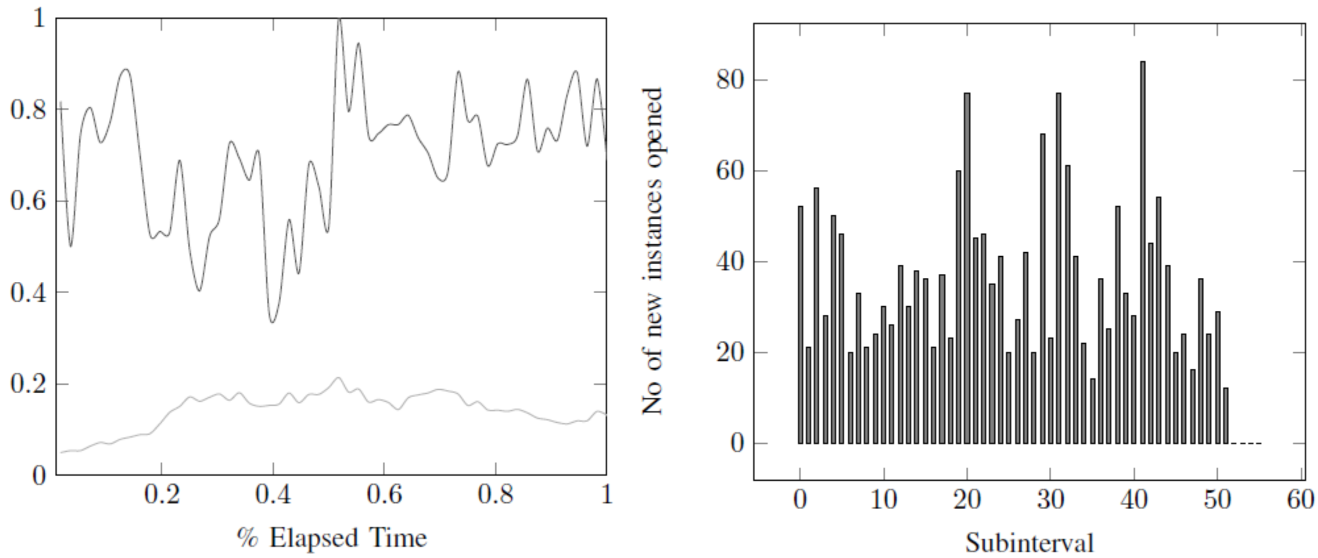

Figure 1b: As with Group 1, in the left graph the darker line reflects the RTM for Group 2 for each of the time subintervals. As can be seen here, RTM is less stable than it is in Group 1. The lighter line reflects the percentage of instances exceeding Lead Time (*avg+k·std*, with *k*=1.5). The right histogram illustrates the number of new instances for each subdivision. As can been seen in the figure, there is negative correlation between RTM and the number of new instances.

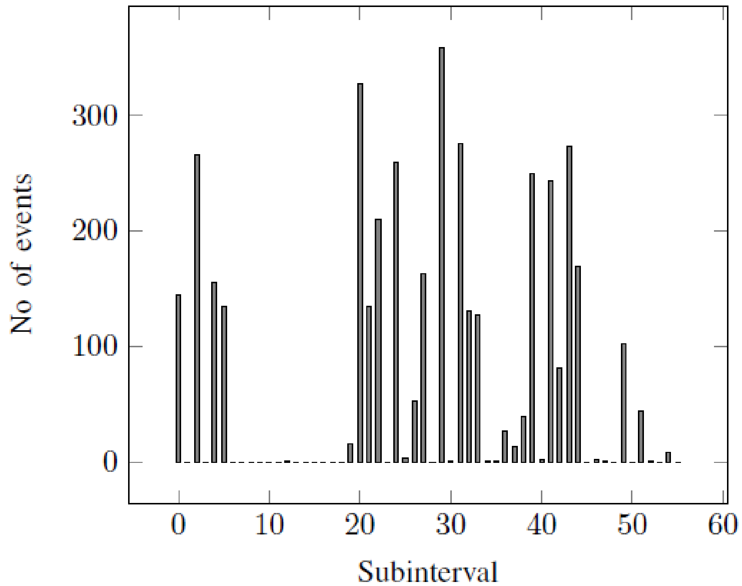

Figure 2: Number of events executed by worker 11179 in each of the temporal intervals. We suspect that this worker is responsible for the sudden decline in RTM evident in Group 2.

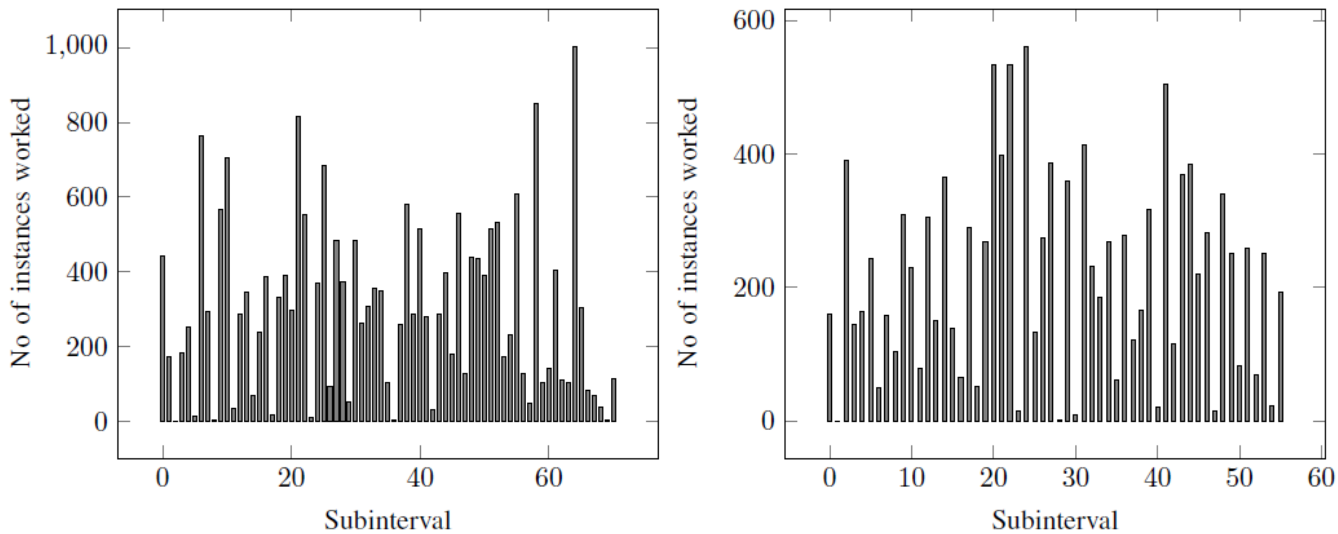

Figure 3: Number of instances worked by each group (histogram on the left side refers to Group 1, while histogram on the right side refers to Group 2) in each of the time subintervals. Group 1 has a typically higher workload than Group 2.

APPENDIX

APA_Prel($\textbf{\textit{LOG}}$,W,N_Subd)

Require: An event log LOG, work group W, number of subdivisions N_Subd of the interval
Ensure: Values of APA_Prel for each sub-interval

$V_0 \leftarrow \emptyset$ ▷ Values of APA_Prel in the subintervals, initially empty
$time\_start \leftarrow \inf\{\rho_t(e), e \in LOG\}$
$time\_stop \leftarrow \sup\{\rho_t(e), e \in LOG\}$
$SD \leftarrow \frac{time\_stop - time\_start}{N\_Subd}$ ▷ Sub-interval duration
for $k = 1, \ldots, N\_Subd$ **do**
  $I \leftarrow [time\_start + (k-1) \cdot SD, time\_start + k \cdot SD]$
  $val \leftarrow \emptyset$ ▷ Values of prevalence of actions for workers in the given subinterval
  $LR \leftarrow LOG_{|\rho_t(e) \in I}$ ▷ Restricted log
  for all $w \in W$ **do**
    $val(k) \leftarrow \max_a \frac{\#\{e \in LR | \rho_a(e) = a, \rho_w(e) = w\}}{\#\{e \in LR | \rho_w(e) = w\}}$
    ▷ Add the prevalence for a given worker
  end for
  $V_0(k) \leftarrow \mathrm{avg}(val)$ ▷ Add the value of APA_Prel for the sub-interval
end for
return V_0

Algorithm 1: to calculate the APA_Prel measure.

APA($\textbf{\textit{LOG}}$,W,N_Subd)

Require: An event log LOG, work group W, number of subdivisions N_Subd of the interval
Ensure: Values of APA for each sub-interval

$V_0 \leftarrow$ APA_Prel(LOG,W,N_Subd) ▷ Values of APA_Prel in the subintervals
$V \leftarrow \emptyset$ ▷ Values of APA in the subintervals, initially empty
$val\_min \leftarrow \min V_0$ ▷ Minimum value of APA_Prel
$val\_max \leftarrow \max V_0$ ▷ Maximum value of APA_Prel
if $val\_min \neq val\_max$ **then**
  for $i = 1, \ldots, |V_0|$ **do**
    $V(i) \leftarrow \frac{V_0(i) - val\_min}{val\_max - val\_min}$
  end for
else
  for $i = 1, \ldots, |V_0|$ **do**
    $V(i) \leftarrow 1$
  end for
end if
return V

Algorithm 2: to calculate the APA measure.

APH_Prel(*LOG*,W,N_Subd)
Require: An event log LOG, work group W, number of subdivisions N_Subd of the interval
Ensure: Values of APH_Prel for each sub-interval
$V_0 \leftarrow \emptyset$ ▷ Values of APH_Prel in the subintervals, initially empty
$time\_start \leftarrow \inf\{\rho_t(e), e \in LOG\}$
$time\_stop \leftarrow \sup\{\rho_t(e), e \in LOG\}$
$SD \leftarrow \frac{time\_stop - time\_start}{N\_Subd}$ ▷ Sub-interval duration
$instance\_ratio \leftarrow \emptyset$ ▷ Handover prevalence ratio for each instance
for $instance \in LOG$ **do**
  $HC \leftarrow handover\_count(instance, W)$
  ▷ Count the handovers, in the instance, between different members of the group
  $NEV \leftarrow events\_count(instance, W)$
  ▷ Count the number of events done, in the instance, by members of the group
  if $NEV > 0$ **then**
    $instance\_ratio(instance) \leftarrow \frac{HC}{NEV}$ ▷ We add the ratio for the instance
  else
    $instance\_ratio(instance) \leftarrow 0$
  end if
end for
for $k = 1, \ldots, N\_Subd$ **do**
  $I \leftarrow [time\_start + (k-1) \cdot SD, time\_start + k \cdot SD]$
  ▷ Put in WI all instances worked in interval, || means OR
  WI $\leftarrow \{instance \in LOG,$
    $instance\_start(instance) \in I$
    $\|\ instance\_stop(instance) \in I$
    $\|\ (instance\_start(instance) \leq \sup(I)$ &&
    $instance\_stop(instance) \geq \inf(I))\}$
  ▷ Instances actively worked in time interval I
  $V_0(k) \leftarrow \text{avg}\{instance\_ratio(i) \mid i \in \text{WI}\}$
  ▷ We do the average of ratios for all worked instances in I
end for
return V_0

Algorithm 3: to calculate the APH_Prel measure.

APH($\boldsymbol{LOG}$,W,N_Subd)
Require: An event log LOG, work group W, number of subdivisions N_Subd of the interval
Ensure: Values of APH for each sub-interval
  $V_0 \leftarrow$ APH_Prel(LOG,W,N_Subd) ▷ Values of APH_Prel in the subintervals
  $V \leftarrow \emptyset$ ▷ Values of APH in the subintervals, initially empty
  $val\_avg \leftarrow \text{avg} V_0$ ▷ Average value of APH_Prel
  $val\_max \leftarrow \max V_0$ ▷ Maximum value of APH_Prel
  for $i = 1, \ldots, |V_0|$ **do**
    if $V_0(i) < val\_avg$ **then**
      $V(i) \leftarrow 1 - 0.5 \cdot \frac{V_0(i)}{val\_avg}$
    else
      $V(i) \leftarrow 0.5 * (1 - \frac{V_0(i) - val\_avg}{val\_max})$
    end if
  end for
  return V

Algorithm 4: to calculate the APH measure.

RTM($\boldsymbol{LOG}$,W,N_Subd)
Require: An event log LOG, work group W, number of subdivisions N_Subd of the interval
Ensure: Values of R.T.M. for each sub-interval
  $V \leftarrow \emptyset$ ▷ Values of R.T.M., initially empty
  $V_1 \leftarrow$ APA(LOG, W, N_Subd)
  $V_2 \leftarrow$ APH(LOG, W, N_Subd)
  for $i = 1, \ldots, N\_Subd$ **do**
    $V(i) = \frac{V_1(i) + V_2(i)}{2}$
  end for
  return V

Algorithm 5: to calculate RTM for each subinterval, given a specified number of subintervals.

NI(***LOG***,W,N_Subd)

Require: An event log LOG, work group W, number of subdivisions N_Subd of the interval
Ensure: Number of new instances, worked by the group, for each subinterval
$V \leftarrow \emptyset$ ▷ Number of new instances, initially set to empty
$time\_start \leftarrow \inf\{\rho_t(e), e \in LOG\}$
$time\_stop \leftarrow \sup\{\rho_t(e), e \in LOG\}$
$SD \leftarrow \frac{time\_stop - time\_start}{N\_Subd}$ ▷ Sub-interval duration
for $k = 1, \ldots, N\_Subd$ **do**
$I \leftarrow [time\_start + (k-1) \cdot SD, time\_start + k \cdot SD]$
▷ We count the number of new instances opened in the interval
$V(i) \leftarrow \#\{\rho_c(e) | \rho_t(e) \in I, \rho_t(e) \leq \rho_t(e') \ \forall e' \in LOG,\ \rho_c(e') = \rho_c(e)\}$
▷ We have added the number of new instances in the given sub-interval
end for
return V

Algorithm 6: to calculate the number of new instances worked by the group for each subinterval, given a number of subintervals.

RTM(***LOG***,W,N_Min_Subd,N_Max_Subd)

Require: An event log LOG, work group W, interval where we want to search for the best number of subdivisions.
Ensure: The values of R.T.M. for the best choice of the number of subdivisions
$corr \leftarrow \emptyset$ ▷ Values of correlations between RTM and NI, given the number of subdivisions; initially empty
for $k = N\_Min\_Subd, \ldots, N\_Max\_Subd$ **do**
$corr(k) = \text{correlation}(\text{RTM}(LOG, W, k), \text{NI}(LOG, W, k))$
▷ We register the Pearson correlation between RTM and NI, given the number of subdivisions
end for
return $\text{RTM}(LOG, W, \text{argmax}_{[N\_Min\_Subd, N\_Max\_Subd]}(corr))$

Algorithm 7: to calculate RTM with optimal number of subintervals.

Stability(***RTM_Values***)

Require: The values of RTM (for the considered number of subdivisions)
Ensure: The stability value
return $1/\text{Variance}(RTM\_Values)$

Algorithm 8: to calculate the stability of RTM.

```
Reactivity(RTM_Values)
Require: The values of RTM (for the considered number of
  subdivisions)
Ensure: The reactivity value
  Sum ← 0
  Count ← 0
  for i = 1, ..., |size(RTM_Values)| do
    if is_local_minimum(RTM_Values,i) then
      k = find_next_local_maximum(RTM_Values, i)
      Sum ← Sum + (k − i)
      ▷ We evaluate the distance between the local minimum and
      the next local maximum
      Count ← Count + 1
    end if
    if Count > 0 then
      return Count/Sum · size(RTM_Values)
      ▷ Effectively do the (inverse) average and give then the value
    else
      return 0
    end if
  end for
```

Algorithm 9: to calculate collective reactivity given an array of values of RTM.