Information Processing and Management 49 (2013) 169–178

Contents lists available at SciVerse ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/infoproman

Temporal modeling of group information foraging: An application to emergency response

Babajide Osatuyi [a,*], David Mendonça [b]

[a] College of Business Administration, Department of Computer Information Systems & Quantitative Methods, University of Texas Pan American, 1201 W. University Drive, Edinburg, TX 78539, United States
[b] Department of Industrial and Systems Engineering, Rensselaer Polytechnic Institute, 110 8th St., Troy, NY 12180, United States

ARTICLE INFO

Article history:
Received 26 October 2010
Received in revised form 31 December 2011
Accepted 1 March 2012
Available online 26 March 2012

Keywords:
Information foraging
Foraging dynamics
Temporal analysis
Time constraint
Group decision making

ABSTRACT

This work seeks to uncover and explain the dynamics of information foraging within small groups. The focus of this work is collaborative information foraging within multidisciplinary emergency response teams during the response to a simulated emergency. The study investigates how such groups distribute their effort between the activities of information seeking and handling (i.e., processing) for information that is unique (i.e., initially held by one member) versus common (i.e., initially held by multiple members). Temporal analysis is applied to the data from a laboratory study of three such groups. The results suggest that temporal analysis may be used to model distribution of effort between seeking and handling, but not how this effort is divided between common versus unique information sources. Opportunities for future research along these lines are identified and briefly discussed.

1. Introduction

Complexity and dynamism are endemic to emergencies, such as those precipitated by natural or man-made disasters (Skertchly & Skertchly, 2001; Weick, 1993, 1995). Rapid and multifaceted changes in the emergency situation create the need for collaboration of emergency response personnel across diverse fields (such as fire, police and medicine), and thus for robust protocols for acquiring and processing information (Ozel, 2001; Weick, 1993). This study attempts to identify and model the factors that can influence these information-intensive processes within groups of emergency response personnel.

The process of information foraging, which typically refers to how information is sought and processed from different sources, is thought to have an impact on the processes and outcomes of group work (Annett, Cunningham, & Mathias-Jones, 2000; Waller, Giambatista, & Zellmer-Bruhn, 1999). Prior research in this area explores information foraging, usually as practiced by individuals, within environments ranging from the World Wide Web (e.g., Pirolli, 2007; Zhang, Jansen, & Spink, 2009) to military command and control (e.g., Sonnenwald & Pierce, 2000). This work has yielded greater conceptual clarity in describing how humans seek and "handle" (i.e., process) information—a joint phenomenon that has been termed "information foraging". It has also articulated a clear need for further work in modeling the effect of exogenous factors on information foraging behavior (e.g., Hansen & Kalervo, 2005), including factors such as time constraint and , group members' roles (Foster, 2004; Reddy & Jansen, 2008; Weick, 1993). When responding to disasters, for instance, possible frequent changes in event severity may influence what information is sought and how it is sought and/or handled. For example, less time is typ-

* Corresponding author.
E-mail addresses: bosatuyi@gmail.com (B. Osatuyi), mendod@rpi.edu (D. Mendonça).

0306-4573/$ - see front matter
http://dx.doi.org/10.1016/j.ipm.2012.03.001

ically spent on assessing resource distribution options later than immediately after the onset of a disaster. This suggests that time is an important factor that shapes information foraging behavior.

The work described here contributes to the burgeoning literature on information foraging in a number of ways. Most importantly, the work described here develops data modeling approaches for group-level information foraging phenomena, thereby extending prior research that has mainly focused on individual-level information foraging (Foster, 2004; Reddy & Jansen, 2008; Weick, 1993), and on the use of multimethod-based techniques based on longitudinal data (Hyldegård, 2009). Additionally, considerable work has been undertaken on examining information foraging outcomes (e.g., appropriateness or quality of information that has been foraged) (Ozel, 2001; Weick, 1993). The present research addresses information foraging at a process-level: that is, one that engages how foraging unfolds over time. Indeed as discussed more fully below, recent research on information foraging by individuals (e.g., Pirolli, 2007; Zhang et al., 2009) suggests that time is indeed a salient factor in explaining foraging processes. The contribution of this research is therefore twofold: it documents a modeling approach for the analysis of foraging activities within groups, and estimates model parameters using process-level data obtained in a structured experimental setting.

The paper proceeds as follows: a background of concepts used in formalizing the phenomena considered in this study is presented in Section 2. The methodology and findings of the study are then described (Section 3), followed by a discussion of study conclusions, contributions and limitations of this research as well as opportunities for extending it (Section 4).

2. Background

This section reviews prior conceptual and empirical work on information seeking and handling, links to information distribution, cast in terms of tasks typically undertaken by emergency response organizations.

2.1. Information foraging

Information foraging is a term used to describe a complex of activities associated with the seeking, gathering, sharing and consuming of information by one or more humans (Pirolli & Card, 1999). Prior and ongoing research has investigated the activities framed by this term, albeit using a somewhat inconsistent terminology. For example, information seeking has also been viewed as information search (Kray & Galinsky, 2003) and information gathering has been denoted information acquisition (Saunders & Miranda, 1998) or information collection (Waller et al., 1999). Information sharing may be viewed as an activity in which information that has been gathered is shared with one or more individuals. These three terms may be used to describe activities that occur between the time an individual decides to seek for information and when the individual decided whether or not to consume (i.e., use) it.

The final activity, information consuming, is closely related to information processing (Dennis, Hilmer, Taylor, & Polito, 1997) and to information recall and use (Dennis, 1996; Dennis et al., 1997). A closer examination of information consuming—particularly in the context of group work—has led to a new term, information handling, which refers to "the physical and mental acts involved in incorporating found information into the group's existing knowledge base" (Wilson, 2000). The view taken here is that it is possible to separate foraging into two qualitatively different activities: those occurring before the information is consumed (i.e., seeking and gathering), and those occurring during and after it is consumed (i.e., consuming and sharing), which are referred to as information seeking and information handling, respectively. One contribution of the work described below is defining and exercising methods for identifying each of these activities in group-level data.

2.2. Group information foraging

Research on information foraging is strongly grounded in individual-level practices, whether exercised independent of others, as in studies of information foraging by individuals via the World Wide Web (e.g., Pirolli, 2007; Zhang et al., 2009) or dependent on others, as in studies of large groups of individuals whose search results are made available to others (Pirolli & Card, 1999), an activity sometimes described as social information foraging. It should be emphasized, however, that social information foraging does not imply explicit collaboration across individuals. In a collaborative setting, individuals coordinate their efforts in order to advance group-level objectives (Annett et al., 2000; Waller et al., 1999). Prior research on group work has identified factors such as complexity of the collective task (e.g., McGrath, 1984; Vakkari, 1999), communication patterns and work activities (Bruce et al., 2003) and spatio-temporal location of group members as relevant to group processes and outcomes (Johnson, 2003; Savolainen, 1999). In sum, these studies point to the need for a proper understanding of the distribution of information among group members in order for the group to be effective in achieving their collective goal.

2.3. Information distribution

Prior studies strongly suggest sharp differences in patterns of human information processing and decision making when the environment in which these activities take place is characterized by dynamism (Brehmer, 1992; Gonzalez, 2004) and high stakes (Klein, Orasnu, Calderwood, & Zsambok, 1993; Perrow, 1984). Indeed, it is well known that—given particular exogenous conditions—information that is held by one member will be unlikely to be shared with others, even when doing so would advance group goals (Stasser, Taylor, & Hanna, 1989; Stasser & Titus, 1987). The collaborative nature of the group task therefore highlights the salience of information distribution to studies of group information foraging behavior. The proportion of group members who hold some information beforehand, determines initial commonality of information (Stasser & Titus, 1987; Stasser et al., 1989). Information items available to groups may be distributed as either unique (i.e., known by one group member) to common (i.e., known by all group members).

2.4. Information foraging in emergency response organizations

In the event of a large-scale emergency, the activities of responding organizations are coordinated by emergency response organizations (EROs) (Mendonça & Wallace, 2007; Stewart & Bostrom, 2002). EROs are typically comprised of representatives from key agencies such as fire, emergency medical technicians, and police (Belardo, Karwan, & Wallace, 1984). Given the high stakes in emergencies, a premium is placed on seeking, handling and managing information in a timely fashion in order to make effective decisions (Klein et al., 1993; Perrow, 1984). Thus EROs may be characterized as information hubs during emergency response, where problems across organizational boundaries are addressed and decisions made under time constraints (Quarantelli, 1978; Scanlon, 1994). These characteristics make EROs well suited for the study of group information foraging.

Information foraged by an ERO may rely on human or non-human sources. Each group member typically holds information that is relevant to the task but differs from or complements information held by others. The proportion of group members who hold some information beforehand determines initial commonality of information (Stasser & Titus, 1987; Stasser et al., 1989).

3. Research objective

The objective of this study is to develop a temporal model for analyzing information foraging behavior of a multi-disciplinary group responding to a simulated emergency scenario. This entails estimating the extent to which time explains the variability in information foraging behavior within a particular group. The following research questions (RQs) guide this investigation:

- RQ1: To what extent do past foraging activities explain current distribution of effort in *foraging* for unique and common information?
- RQ2: To what extent do past foraging activities explain *seeking* for common versus unique information?
- RQ3: To what extent do past foraging activities explain *handling* of common versus unique information?

Time series analysis is used to address these questions as it holds the potential to model temporal factors that underlying information foraging activities.

4. Study design

This study employs a controlled laboratory experiment in which a group of emergency response personnel interact with each other in relation to a simulated emergency environment. The group's task is to allocate resources to an incident location in order to meet the goals of the emergency response. Information relevant to the case is available through a computer interface, and can be discussed among participants. All conversations are video and audio taped, and all direct manipulations of the computer interface are logged for analysis.

4.1. Participants and roles

Participants were emergency managers taking part in a training course at the US National Fire Academy (NFA). Each group consists of five roles: one group coordinator (CO), and one representative from each of the following four emergency services: Police Department (PD), Fire Department (FD), Medical Officer (MO) and Chemical Advisor (CA). All participants had at least 10 years of experience in their organization, and reported having participated in tens to hundreds of exercises, as well as responding to thousands of emergencies.

4.2. Experiment design

The group convened in a conference room, seated so that they could view each other face-to-face, with video cameras and microphones set up to record their interactions. The group was first presented with an overview of the session, the completed consent forms and background questionnaires. They next chose their roles, based on their area of expertise, and practiced using the computer-based system on a test case until all stated that they understood their task and how to use the simulated environment to perform it. They were then presented with the information on the case.

4.3. Task and simulation environment

The task of the group concerned a cargo ship fire with subsequent oil spill. Case materials were developed from archival reports of prior incidents, supplemented by discussions with subject matter experts. The group's task was to allocate resources to the incident in order to meet four response goals: (1) control of access to incident location; (2) control of fire at incident location; (3) removal of trapped persons from danger; and (4) treatment of injured persons. Information on the case was presented through a computer interface (see Fig. 1) with a map on the left side showing the location of available resources and panels with information about the status of the emergency on the right. Icons on the map serve as aides to resources that are controllable by a particular discipline. Information about other resources associated with another role had to be requested verbally. The CO had access to all information pertaining to the case.

4.4. Study data

Study data are taken from two complementary sources: logs of group members' interaction with the simulation, and transcribed records of conversation among group members, coded for content to permit data analysis. As shown in Table 1, the column *Source* indicates whether the data were taken from the log of interaction with the computer (*L*) or from the conversation transcript (*T*).

For the logs, an entry was generated whenever a group member clicked on a site (*Site*) or the Goal (*Goal*) button. Also written to the file was the time of the click in seconds since onset of the case (*Time*), along with other data such as the session, group and participant role (*Role*). *InfoType* indicates whether the information was initially common or unique, while *Behavior* indicates whether the item was sought or handled. As an example, the second record in Table 1 shows that participant FD sought information on site B (see Fig. 1) via the computer interface at time 22. This information item (here, a fire truck) is coded as initially *unique* since it is only visible to the FD. Note that the information item becomes common when it is announced to the group at time 35. In other words, an information item is common to every member of the group if is communicated to the group at the beginning of the experiment; otherwise, it is unique.

For the transcripts, an instrument was developed for identifying and classifying details of the activities of information seeking and handling. *Information seeking* refers to purposive search for information, and is said to occur when in the following instances: questions requesting information from other group members; responses to such inquiries; other provision of information to group members. *Information handling* refers to the incorporation of found information into existing knowledge, and is said to occur in the following instances: statements concerning the allocation of resources; suggestions about courses of actions that may be submitted; explanations about allocation of resources and/or submissions of courses of action; and evaluations and confirmations concerning any allocation of resources and/or accomplishment of goals.

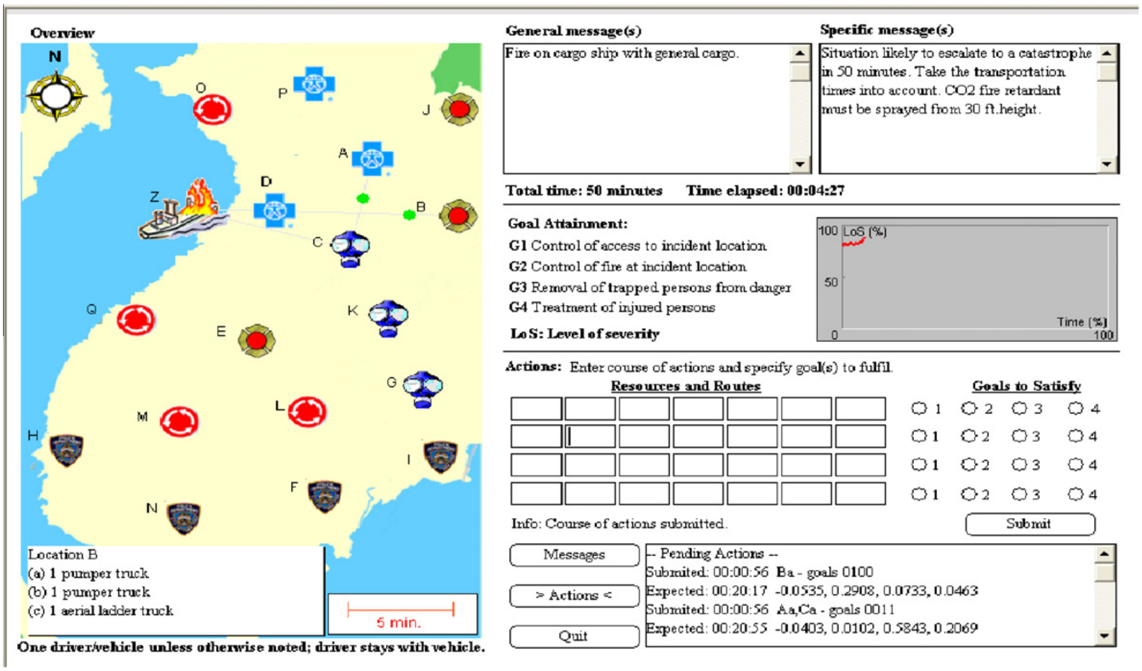

Fig. 1. Interface to the simulation.

Table 1
Selected records from merged log and transcript files.

Time (s)	Source	Role	Site	Resource	InfoType	Behavior
20	L	CO	Q	–	C	S
22	L	FD	B	Fire truck	U	S
25	L	MO	P	-	U	S
30	T	CA	C	Gas masks	U	H
35	T	FD	A	Fire truck	C	H

Table 1 illustrates the data from this study. For example, record 1 shows that, at 20 s (*Time*) into the session, the coordinator (*Role* = CO) clicked on site "Q". *Source* is therefore the log file—"L", and the information about that site was held in common, so that *InfoType* is "C", a *Behavior* classified as information seeking ("S"). As a second example, at 30 s, the participant in the role of CA handled the unique information item "gas masks at Site C". For the transcript data, two independent coders identified and classified instances of information foraging activities, with resulting inter-coder reliability above 80% for all transcripts. Each statement in the transcript was time-synchronized with the corresponding computer log files to the level of seconds before being analyzed. Data from the three experiments are independently used to estimate parameters of the proposed model.

5. Methodology

The methodology for this study—time series analysis—enables identification and estimation of temporal effects of prior foraging behavior on current foraging behavior. This problem arises in numerous situations, particularly those where behavioral patterns are suspected to be cyclical or otherwise temporally patterned (e.g., systematically increasing or decreasing over time). In contrast, typical approaches to the analysis of foraging data focus on pre- and post-foraging measures (e.g., net change in the number of information targets retrieved). Time series models seek to account directly for serial dependency (autocorrelation) in the data, allowing for prediction of future foraging behavior without an attempt to measure independent relationships that influence it (Linden, 2003; SAS Institute Inc, 1996). An advantage of time series-based models is that they enable consideration of temporal factors that cannot be captured via pre-/post-techniques such as ANOVA, but within the framework of traditional hypothesis testing. The interpretation of time series analyses tends to focus on the duration and amplitude of cyclical trends in the data, as well as on overall increases or decreases in the value of the variable(s) under study. For example, time series analysis may be employed to identify whether foraging effort oscillates, and if so over what period. It may also be employed to identify whether foraging effort decreases or increases overall, thus providing a degree of continuity with pre-/post-techniques.

The Autoregressive Integrated Moving Average (ARIMA) time series modeling approach (Box & Jenkins, 1976) includes both autoregressive (p) and moving average parameters (q) as well as differencing (d) in the formulation of the model, and may be summarized using the notation ARIMA (p, q, d); p is the number of autoregressive terms, d is the number of non-seasonal differences and q is the number of lagged forecast errors in the prediction equation. For example, given a time series process y_t, a first order autoregressive process is denoted as ARIMA (1,1,1) or simply AR (1,1) means that it contains 1 autoregressive parameter and 1 moving average parameter after it was differenced once to attain stationarity. Equation 1 shows that the time series has one period ahead y_{t-1} relationship with its current value y_t.

$$y_t = \phi_0 + \phi_1 y_{t-1} + \varepsilon_t \tag{1}$$

ϕ_0, ϕ_1 are constants; $|\phi_1| < 1$, high value of ϕ_1 denotes strong serial dependency in the series data, ε_t is assumed to be a white noise series $\varepsilon_t \sim N(0, \sigma_a^2)$.

Box and Jenkins (1976) provide detailed procedure of estimating goodness of fit and parameter estimates of ARIMA models consisting of the following steps: model identification, model parameter estimation, and model diagnostics. Model identification examines the data to identify appropriate procedures for achieving stationarity in the time series being investigated. It also yields the order of the regular and seasonal auto regressive and moving average polynomials that is necessary to represent the time series model. The Autocorrelation Function (ACF) measures the amount of linear dependence between observations in a time series that are separated by a lag k. The Partial Autocorrelation Function (PACF) plot helps to determine the number of autoregressive terms necessary to reveal one or more of the following characteristics: time lags where high correlations appear, seasonality of the series, trend either in the mean level or in the variance of the series.

Model parameter estimation yields values that minimize the Sum of the Squared Residuals (SSR) between the real data and the estimated values. In general, a non-linear, maximum-likelihood estimation method is used.

Model diagnostic procedures are used to examine the adequacy of the residual error from the fitted model, typically accomplished by examining residual ACF plots and by conducting formal goodness-of-fit tests. If the residuals are correlated, then the model should be refined as in step 1 above. Otherwise, the autocorrelations are regarded white noise and the modeling process is concluded.

Time series analysis requires equal time periods between observations. Here, a time period of 15 s was used (this time period covered approximately five conversation turns on average). All statistical calculations were performed using PROC ARIMA in SAS v.9.1.

6. Results

A summary of results from the three sessions is first provided, followed by a discussion of their interpretation. All statistical tests were performed at $\alpha = 0.05$ unless otherwise noted.

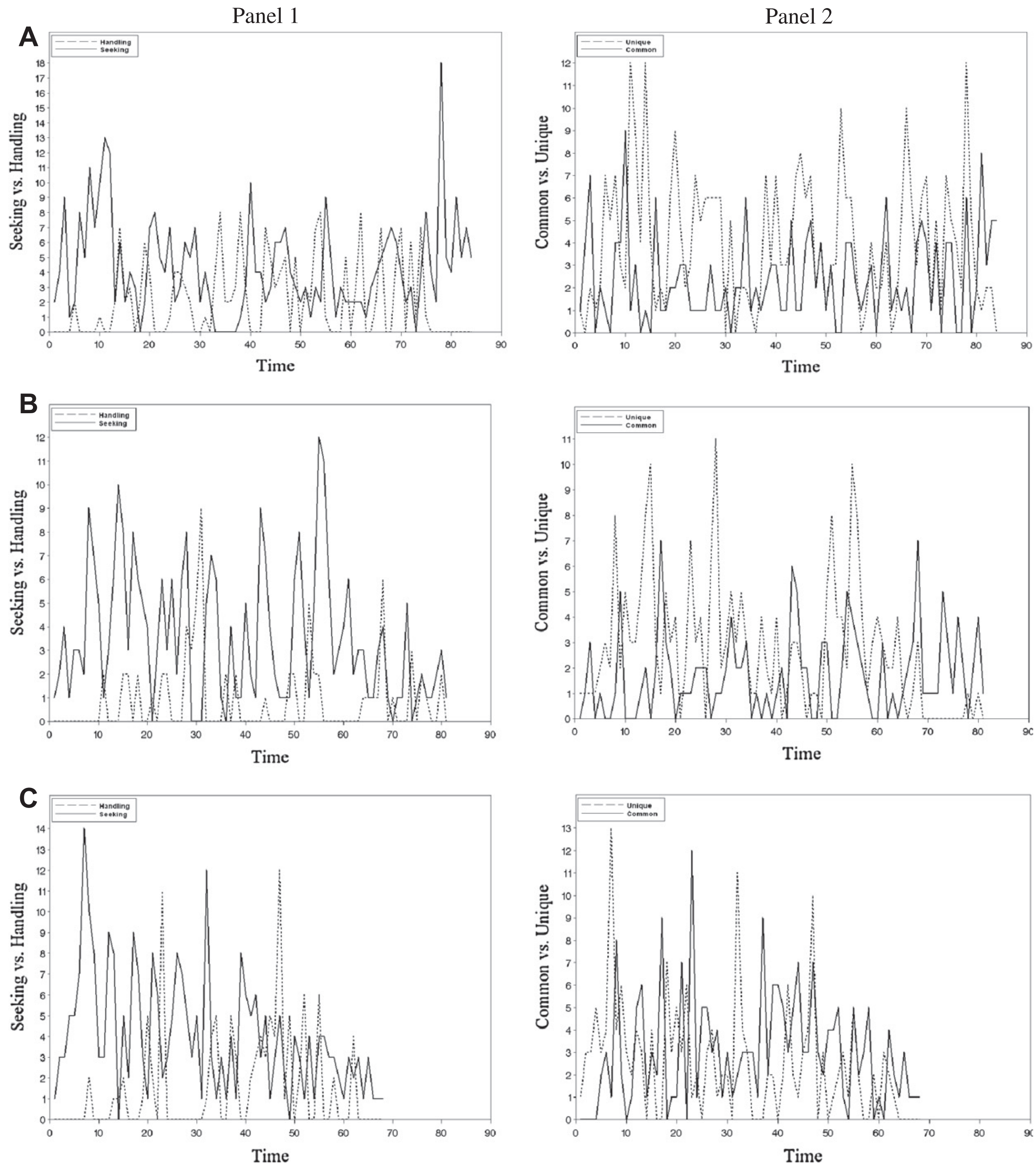

Fig. 2. Seeking versus handling for all information (panel 1); foraging for common versus unique information (panel 2), for groups A, B and C, over time.

Data are summarized in Fig. 2. The right panel in Fig. 2 shows the number of foraging activities (i.e., combined seeking and handling activities) for common versus unique information at each interval for each group. For instance, there were seven and two instances of foraging for common and unique information items, respectively, in the second time interval in group *A*. The left panel in Fig. 2 shows the number of seeking versus handling activities in each interval for each group. For example, in the first time interval there were 2 instances of information seeking in group *A*.

Consistent with time series analysis methodology, the following analyses are performed to address the research questions. The first is an attempt to model foraging for common versus unique information (RQ1); the second is an attempt to model seeking versus handling activities, ignoring whether the information being sought or handled is common or unique (RQs 2 and 3).

6.1. Foraging for unique versus common information

The data for addressing RQ1 are those shown on the right panel in Fig. 2. It may be noted that foraging for unique information generally exceeds foraging for common information across all groups. The relevant data are captured in a single variable by modeling the proportion of foraging effort devoted to common versus unique information. However, the model identification phase reveals that this variable is non-stationary (Box & Jenkins, 1976) for all three groups, strongly suggesting that a Box–Jenkins approach is not appropriate. It may therefore be concluded that past foraging activities do not explain distribution of the group information foraging effort for common versus unique sources.

6.2. Effort devoted to seeking versus handling

The data for addressing RQs 2 and 3 are those shown on the left panel in Fig. 2. The patterns here differ in morphology. For group *A*, seeking activities peak in the earlier and later stages of the session; for group *B*, they peak in the earlier and middle stages; for group *C*, they peak in the earlier stages, then generally decrease. Handling activities are perhaps more difficult to characterize: *A* appears to occupy a narrow range, while those for groups *B* and *C* rise with no readily discernible pattern.

Apparent in all three series is a stronger pattern of peaks and valleys without appreciable upward or downward trends. As in the first analysis, the data are expressed in terms of a single variable. Here, the data are modeled using the product (p^*) of (1) the estimated proportion of seeking activities and (2) the estimated proportion of handling activities ($\ddot{p}_S = n_S/n_{S+H}$ and $\ddot{p}_H = n_H/n_{S+H}$, respectively). Application of the Box–Jenkins procedure shows that p^* exhibits stationarity and that there is no drift in the data, suggesting that prior values of p^* can indeed be used to model future ones.

Having identified that an ARIMA model may be appropriate, parameters are estimated as follows. To estimate the autoregressive parameter (p), a partial autocorrelation plot is used (see Fig. 3). The plot enables visual identification of the lag

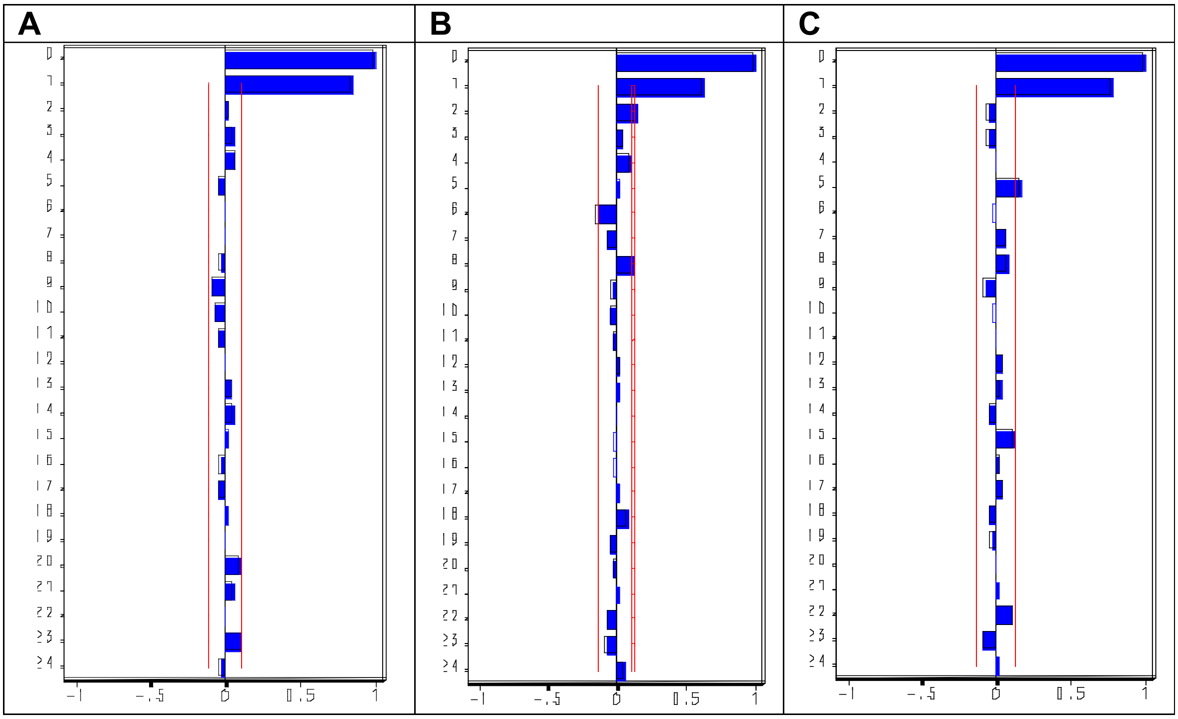

Fig. 3. Partial Autocorrelation Function (PACF) plot of correlation coefficients.

value (shown on the vertical access) associated with values of the autocorrelation that exceed zero by two standard errors. As shown in Fig. 3, this value is unity (1). The moving average parameter, q, can also be estimated using Fig. 3. The standard interpretation of data like those presented in Fig. 3 is that the decay in the value of the correlation value is exponential in nature (Box & Jenkins, 1976), leading to the conclusion that $q = 0$. As mentioned previously, a differencing of unity has been used for these data, so that the final ARIMA parameter, d, is equal to unity. Subsequent diagnostic tests confirm these results, suggesting that the appropriate model for the data is ARIMA(1,0,1).

To complete the analysis, the data were fitted to the ARIMA model using maximum likelihood estimation methods (Box & Jenkins, 1976), producing the following results for each group:

$$p_t^* = 0.09014 + 0.26406 \times p_{t-1}^* \tag{2}$$

$$p_t^* = 0.05534 + 0.26025 \times p_{t-1}^* \tag{3}$$

$$p_t^* = 0.06888 + 0.255590 \times p_{t-1}^* \tag{4}$$

The above models suggest that foraging activity in the current period, when expressed as a function of seeking versus handling, is significantly related to foraging activity in the previous period. Moreover, the model suggests that the value of p^* is actually decreasing overall over time (the value of p^* is always between zero and unity). Foraging activity is therefore said to decrease over time, as discussed more fully in the following section.

7. Discussion

7.1. Foraging for unique versus common information

The results show that distribution of information foraging effort across unique and common sources is not time dependent—despite the strong time constraints built into the experiment task. This result mirrors those typically seen when data are aggregated across all time periods in the task (e.g., Stasser, Vaughan, & Stewart, 2000), and thus further suggest that groups' preference for unique over common information may be time-invariant.

It is also instructive to reflect on the relationship between this conclusion and performance of the experiment task. Many crucial decisions (e.g., transport of the Medical Officer's CO_2 to the incident location) could not be accomplished without extracting (and using) unique information from other participants (e.g., identifying possible means for transporting CO_2 to the incident location by, say, querying the Fire Department about the operational status of its ladder trucks—a unique information item). To determine if participant role is associated with distribution of foraging effort across unique and common sources, the following exploratory test is undertaken. A reasonable null model is one of independence between role of forager and type of information, yielding a 5×2 contingency table. The data are first cross-classified to provide counts of seeking and foraging activities by role, aggregated across all time periods. Pearson's Chi-square test of independence (Chernoff & Lehmann, 1954) is used to test the null hypothesis of independence between the two dimensions. The resulting p-value of 0.0892 offers some weak support that division of foraging effort across unique versus common sources is shaped by role.

7.2. Information seeking versus handling

In contrast to the results for foraging of common versus unique information, the results for information seeking versus handling show a significant and strong temporal dependency: as time passes, foraging activity decreases. The specific amount of decrease in the current time period is a function of foraging in the previous time period (multiplied by a constant). This result extends previous research by explicitly modeling a process suggested by (Blumberg, 1994). So, while a stage model of some type may help explain division of effort between common and unique sources, it is the factor of time that explains division of effort between information seeking versus information handling, answering research questions 2 and 3.

From the broader perspective of collaboration or group work, the data and results strongly suggest interplay between seeking and handling activities. There are no periods where one of these activities clearly dominates the other. It is also immediately obvious from the raw data that there is frequent switching between seeking and handling activities. In a dynamic decision making environment, the information space may be changing as new information is created (e.g., by combining existing information) and other information is lost or becomes outdated. It may therefore be beneficial for collaborative foraging tools to provide some mechanism for buffering the information space, as well as tools for operating upon it (either for seeking or handling) (for more on this point, see recent discussions in this direction by Foley and Smeaton (2008) and by Sarcevic (2009).

7.3. Overall observations

Taken together, the results for these data suggest first that, for these data, ARIMA-type models are not appropriate for modeling foraging activity devoted to common versus unique information. Because no trend has been detected, the results do not support an earlier contention that groups are thought to devote more time and effort to seeking common information early in the group decision making process (Larson Jr., Foster-Fishman, & Keyes, 1994). However, ARIMA-type models may be appropriate for modeling distribution of effort between seeking and handling activities, ignoring whether the information being sought and handled is common or unique.

This study also confirms prior research by providing empirical evidence for collaborative strategies that groups employ to make decisions by compromising the tradeoff of qualitative decision-making with time scarcity (Johnson, Giraldeau, & Grant, 2001; Johnson, 2003; Savolainen, 1995, 1999). As such, design of systems to support collaborative information foraging, especially in time critical domains, should incorporate high efficiency in computing and assessing potential resource allocation alternatives in order to minimize the tendency of group members to resort to a less effective collaborative strategy (Janis, 1972; Vakkari, 1999).

8. Conclusions

This study has examined the possibility that a single variable—time—may explain variability within group information foraging behavior. The process-oriented approach taken here is in contrast to difference-based approaches such as ANOVA that estimate aggregate differences between experimental conditions—as opposed to changes within those conditions. The results show that time may indeed be a valuable predictor of foraging effort, though not of the distribution of that effort between common versus unique information.

These results speak not only to some of the methodological issues and opportunities in modeling foraging behavior, but also to implications for practice. As stated at the onset, emergency response organizations (EROs) are relied upon to seek and handle information from a potentially complex and evolving array of sources. Understanding the determinants of foraging behavior should lead to guidelines on how to conduct training and how best to address operational needs in the field.

With regard to training, the approach taken here offers the opportunity for close examination of information foraging, but of course entails a tradeoff in external validity (or transferability) of the results. As has been noted elsewhere (Mendonça & Fiedrich, 2006), a systematic approach of the design of training environments relative to training goals should be taken if approaches such as this one are to be applied with success in practice.

With regard to operational needs, the results suggest that tools to support collaborative information foraging should encapsulate or afford some degree of temporal awareness. The presence of temporal dependency in foraging activity in this study, for example, may be viewed as indicative of the highly time-dependent nature of ERO work processes in general. In stark contrast to tools designed with little or no regard for time constraint, tools for operational ERO use should be structured around the assumption that unconstrained divergent thinking (i.e., seeking) will lead to situations where there is little or no time left for convergent thinking (i.e., both information handling and choice/decision making).

References

Annett, J., Cunningham, D., & Mathias-Jones, P. (2000). A method for measuring team skills. *Ergonomics, 43*(8), 1076–1094.

Belardo, S., Karwan, K. R., & Wallace, W. A. (1984). An investigation of system design considerations for emergency management decision support. *IEEE Transactions on Systems, Man, and Cybernetics: Part A, 14*(6), 795–804.

Blumberg, H. H. (1994). Group decision making and choice shift. In A. P. Hare, H. H. Blumberg, M. R. Davies, & M. V. Kent (Eds.), *Small group research: A handbook* (pp. 141–154). NJ: Ablex Publishing Company.

Box, G. E. P., & Jenkins, G. M. (1976). Time Series Analysis: Forecasting and Control. San Francisco: CA: Holden-Day.

Brehmer, B. (1992). Dynamic decision making: Human control of complex systems. *Acta Psychologica, 81*(3), 211–241.

Bruce, H., Fidel, R., Pejtersen, A. M., Dumais, S., Grudin, J., & Poltrock, S. (2003). A comparison of the collaborative information retrieval behaviors of two design teams. *New Review of Information Behaviour Research: Studies of Information Seeking in Context, 4*(1), 139–153.

Chernoff, H., & Lehmann, E. L. (1954). The use of maximum likelihood estimates in $\chi 2$ tests for goodness-of-fit. *The Annals of Mathematical Statistics, 25*(3), 579–586.

Dennis, A. R. (1996). Information exchange and use in group decision making: You can lead a group to information, but you can't make it think. *MIS Quarterly, 20*(4), 433–457.

Dennis, A. R., Hilmer, K. M., Taylor, N. J., & Polito, A. (1997). Information exchange and use in GSS and verbal group decision making: Effects of minority influence. In: Paper Presented at the 30th Hawaii International Conference on System Sciences, Maui, Hawaii, USA.

Foley, C., & Smeaton, A. F. (2008, June 16–20). Evaluation of coordination techniques in synchronous collaborative information retrieval. In: Paper Presented at the First International Collaborative Search Workshop, Joint Conference on Digital Libraries, Pittsburgh, PA.

Foster, A. (2004). A nonlinear model of information-seeking behavior. *Journal of the American Society for Information Science and Technology, 55*(3), 228–237.

Gonzalez, C. (2004). Learning to make decisions in dynamic environments: Effects of time constraints and cognitive abilities. *Human Factors, 46*(3), 449–460.

Hansen, P., & Kalervo, J. (2005). Collaborative information retrieval in an information-intensive domain. *Information Processing & Management, 41*, 1101–1119.

Hyldegård, J. (2009). Beyond the search process: Exploring group members' information behavior in context. *Information Processing & Management, 45*(1), 142–158.

Janis, I. L. (1972). *Victims of groupthink*. Boston: Houghton Mifflin Company.

Johnson, D. (2003). On contexts of information seeking. *Information Processing & Management, 39*(5), 735–760.

Johnson, C. A., Giraldeau, L.-A., & Grant, J. W. A. (2001). The effect of handling time on interference among house sparrows foraging at different seed densities. *Behaviour, 138*(5), 597–615.

Klein, G. A., Orasnu, J., Calderwood, R., & Zsambok, C. E. (1993). *Decision making in action: Models and methods*. Norwood, NJ: Ablex Publishing Corp..

Kray, L. J., & Galinsky, A. D. (2003). The debiasing effect of counterfactual mind-sets: Increasing the search for disconfirmatory information in group decisions. *Organizational Behavior and Human Decision Processes, 91*(1), 69–81.

Larson, J. R., Jr., Foster-Fishman, P. G., & Keyes, C. B. (1994). Discussion of shared and unshared information in decision-making groups. *Journal of Personality & Social Psychology, 67*(3), 446–461.

Linden, A. (2003). Using Time Analysis for Evaluating Disease Management Program Effectiveness. Paper Presented at the Academy Health Meeting.

McGrath, J. E. (1984). *Groups: Interaction and performance*. Englewood Cliffs, NJ: Prentice-Hall.

Mendonça, D., & Fiedrich, F. (2006). Training for improvisation in emergency management: Opportunities and limits for information technology. *International Journal of Emergency Management, 3*, 348–363.
Mendonça, D., & Wallace, W. A. (2007). A cognitive model of improvisation in emergency management. *IEEE Transactions on Systems, Man and Cybernetics, Part A, 37*(4), 547–561.
Ozel, F. (2001). Time pressure and stress as a factor during emergency egress. *Safety Science, 38*(2), 95–107.
Perrow, C. (1984). Normal Accidents. USA: Basic Books.
Pirolli, P. (2007). *Information foraging theory: Adaptive interaction with information*. New York: Oxford University Press.
Pirolli, P., & Card, S. K. (1999). Information foraging. *Psychological Review, 106*(4), 643–675.
Quarantelli, E. L. (1978). Uses and Problems of Local EOC's in Disasters (No. 53). Newark, DE: Disaster Research Center.
Reddy, M. C., & Jansen, B. J. (2008). A model for understanding collaborative information behavior in context: A study of two healthcare teams. *Information Processing & Management, 44*(1), 256–273.
Sarcevic, A. (2009). A study of collaborative information behavior in trauma resuscitation. Collaborative Information Behavior Workshop at Group 2009.
SAS Institute Inc (1996). *Forecasting examples for business and economics using the SAS system*. Cary, NC: SAS Institute Inc..
Saunders, C., & Miranda, S. (1998). Information acquisition in group decision making. *Information & Management, 34*(2), 55–74.
Savolainen, R. (1995). Everyday life information seeking: Approaching information seeking in the context of "way of life". *Library & Information Science Research, 17*(3), 259–294.
Savolainen, R. (1999). The role of the internet in information seeking. Putting the networked services in context. *Information Processing & Management, 35*(6), 765–782.
Scanlon, J. T. (1994). The role of EOC's in emergency management: A comparison of canadian and American experience. *International Journal of Mass Emergencies and Disasters, 12*(1), 51–75.
Skertchly, A., & Skertchly, K. (2001). Catastrophe management: Coping with totally unexpected extreme disasters. *Australian Journal of Emergency Management, 16*(1).
Sonnenwald, D. H., & Pierce, L. G. (2000). Information behavior in dynamic group work contexts: Interwoven situational awareness, dense social networks and contested collaboration in command and control. *Information Processing & Management, 36*(3), 461–479.
Stasser, G., Taylor, L. A., & Hanna, C. (1989). Information sampling in structured and unstructured discussions of three- and six-person groups. *Journal of Personality and Social Psychology, 57*(1), 67–78.
Stasser, G., & Titus, W. (1987). Effects of information load and percentage of shared information on the dissemination of unshared information during group discussion. *Journal of Personality and Social Psychology, 53*(1), 81–93.
Stasser, G., Vaughan, S. I., & Stewart, D. D. (2000). Pooling unshared information: The benefits of knowing how access to information is distributed among members. *Organizational Behavior and Human Decision Processes, 82*, 102–116.
Stewart, T. R., & Bostrom, A. (2002). *Extreme event decision making: Workshop report*. Albany, NY: University at Albany.
Vakkari, P. (1999). Task complexity, problem structure and information actions: Integrating studies on information seeking and retrieval. *Information Processing & Management, 35*(6), 819–837.
Waller, M. J., Giambatista, R. C., & Zellmer-Bruhn, M. E. (1999). The effects of individual time urgency on group polychronicity. *Journal of Managerial Psychology, 14*(3/4), 244–257.
Weick, K. E. (1993). The collapse of sensemaking in organizations: The mann gulch disaster. *Administrative Science Quarterly, 38*(4), 628–652.
Weick, K. E. (1995). South canyon revisited: Lessons from high reliability organizations. *Wildfire, 4*(4), 54–68.
Wilson, T. D. (2000). Human Information Behavior. *Information Science, 3*(2), 49–56.
Zhang, Y., Jansen, B. J., & Spink, A. (2009). Time series analysis of a Web search engine transaction log. *Information Processing and Management, 45*(2), 230–245.