Writing with Collaborative Hypertext: Analysis and Modeling

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This work explores a novel approach to the analysis and modeling of computer supported collaborative writing. The aim of this dynamic modeling approach is to capture the structure of user behavior as they interact with a computer system. Markov chains models are derived from the empirical data on the use of the system. These models are compared so as to highlight how the dynamic structure of collaborative writing is affected by factors such as the level of users' experience with the system and workspaces for different writing projects. A workspace is associated with a collaborative writing project in terms of both its structure and content. The study shows that the patterns of interactive behaviors of the users were clearly influenced by the system design. Users' experience and workspaces both significantly affected the structure of interactive behaviors in collaborative writing. Users intensively used the system for exploration, organization, and composition tasks in collaborative writing, whereas the use of collaboration facilities of the system was transient in nature. The descriptive–prescriptive nature of the approach has the advantage of reducing the complexity of computer supported collaborative writing down to a more manageable level at which investigators can concentrate more directly on the essence of the dynamics. The experience from the study suggests that this approach is worth pursuing, and it may be fruitfully generalized by integrating with other process modeling techniques and the mainstream practice of software engineering.

Introduction

Researchers in computer supported cooperative work (CSCW) and human–computer interaction (HCI) have recognized the fundamental challenge of building computer systems for highly dynamic and complex group work. Such systems may be used for collaborative design projects, information-intensive decision-making, and collaborative writing. The challenge is to bridge the gap between dynamic and formal aspects of computer supported cooperative work. For instance, this challenge is highlighted by the *situated actions* paradigm, which emphasizes the contingent nature of the organization and evolution of highly interactive work with computers (Suchman, 1987). The dynamic and adaptive nature of human–computer interaction has been regarded as a key to an understanding of collaborative work and to the success of systems design (DeSanctis & Poole, 1994). Investigators are searching for appropriate and efficient approaches to tackle the challenge (Zigurs, 1993).

Olson, Herbsleb, and Rueter (1994) have noted that the effects of technology on work tend to be investigated in terms of the quality of the work done, the satisfaction of those using the technology, or the long-term organizational acceptance of the technology, whereas fewer studies have focused on the details of the process of interacting with the technology or on how the organization of the work itself is affected. Interactive technologies are likely to influence the structure of interactive behaviors of users, and a dynamic model is a major source of clues for researchers to understand how the work is affected by the technology.

Collaborative writing presents a significant challenge to the design and use of information technologies for group work (Kraut, Galegher, Fish, & Chalfonte, 1992; Rimmershaw, 1992). Very little is known about collaborative writing, about the structure of interactive behaviors of users with a computer system, and how the structure is affected by various factors. Recent reviews show that the majority of previous CSCW studies have concentrated on design issues of the computer systems from engineering perspectives (McCarthy, 1994) and that there is a need for theories and models of the users working with groupware (Olson et al., 1993a).

This article focuses on a novel approach to the study of collaborative writing. The study concerns the dynamic nature of collaborative writing, how the nature can be effectively captured, and potentials that the novel approach has shown. To deal with the dynamics and complexity, the power of formal approaches may be strengthened by stochastic analysis and modeling techniques. Markov chain models have the heuristic power to support a descriptive–prescriptive approach. Studying the structure of collaborative writing as a stochastic process can benefit from the existing apparatus of Markov analysis and lend the resultant models to empirical validation.

In our study, occurrences of interactive events in collaborative writing with a collaborative hypertext system are conceptualized as a stochastic process. This conceptualization opens opportunities of combining mathematics, stochastic process analysis, and empirical approaches in the study of collaborative writing. In terms of mathematical and probabilistic models, some important theoretical and practical issues can be addressed in this framework, for example:

- What is an appropriate state space for describing the structure of collaborative writing?
- How can this state space be derived from empirical data?
- Can the essence of computer supported collaborative writing be captured by a Markov model?
- Can a state space be decomposed into some smaller and independent state spaces so that researchers can focus on specific aspects of collaborative writing at a time?

These questions have profound implications for understanding the dynamics of collaborative writing and for integrating several existing methodologies into a new, efficient approach to the study of computer supported collaborative work.

Once the appropriate model is verified, behavioral patterns in collaborative writing are examined based on the descriptive–predictive second-order Markov model. Models for users with different levels of experience with the collaborative hypertext system are compared on the hypothesis that they represent behavioral patterns of different nature. Furthermore, Markov chain models of collaborative writing in workspaces associated with different collaborative writing projects are compared to investigate the effect of a workspace as a whole on users' interactive behaviors in collaborative writing. The study also addresses some particular issues, such as frequently used functions of the system, how these functions are related one another in collaborative writing, and implications of the identified sequential structure for the design and the work.

Computer Supported Collaborative Writing

Computer supported collaborative writing has been studied from a variety of perspectives (Beck & Bellotti, 1993; Chen, Rada, & Zeb, 1994; Haha, Jarke, Eherer, & Kreplin, 1991; Neuwirth, Kaufer, Chandhok, & Morris, 1990, 1994; Posner & Baecker, 1992; Sharples, 1991). It has been realized that there is a particular need for theories and models of collaborative writing (Olson et al., 1993a). On the other hand, researchers have encountered a great challenge in capturing and formalizing the essence of computer supported collaborative writing.

The difficulty of capturing the nature of computer supported collaborative writing seem to be amplified by three interrelated factors. Firstly, the number of collaborative writing systems in real use is still relatively small. Secondly, few existing systems have been used long enough to allow systematic empirical evaluation. Finally, the power of existing modeling techniques seem to be inadequate when it comes to meet the dynamics, complexity, diversity, and scope of collaborative writing. A new and powerful approach is needed as well as detailed descriptions of interactive behaviors.

The notion of hypertext has played a significant role in the design of collaborative writing systems. Hypertext-based collaborative writing systems can be divided into two generations according to their underlying theoretical models of collaboration (Chen & Rada, 1996). In the first generation, hypertext systems do not explicitly deal with interactions in collaborative writing. These systems depend on established protocols of collaboration and pragmatic considerations for coordinating collaborative work. Collaborative hypertext shares some problems with hypertext of previous generations. For example, disorientation is more likely to occur as the information space changes because of concurrent interactions of others associated with the shared workspace (Chen et al., 1994). In collaborative use of NoteCards, a special area was opened in the hypertext-based, shared information space for coauthors to communicate with each other and authors also used different fonts to distinguish their contributions (Irish & Trigg, 1989).

In the second generation, hypertext systems start to address collaboration issues more explicitly and provide some dedicated system functions for collaboration. For instance, an Issue-Base Information System (IBIS) model was used to facilitate argumentation in early stages of collaboration such as brainstorming and planning (Conklin & Begeman, 1988). The Neptune system used the concept of *context*, a collection of nodes and links that must evolve consistently, to facilitate transitions between individual and shared work (Delise & Schwartz, 1987). Some basic mechanisms such as conflict detection in terms of versioning trees are provided to facilitate mutual intelligibility among coauthors. The design of the SEPIA system was based on a coupling model (Haake & Wilson, 1992). In SEPIA, interactive behaviors in collaboration are modeled by three modes in which collaborators may be engaged: Independent, loosely-coupled, or tightly-coupled mode.

SEPIA is a cooperative hypermedia authoring environment (Haake & Wilson, 1992). The nature of interactive behaviors is modeled by independent, loosely-coupled, and tightly-coupled modes. SEPIA provides four activity spaces for collaborative writing: 1) Planning space, 2) content space, 3) argumentation space, and 4) rhetorical space. The system helps monitoring and organizing interactions among coauthors.

Ede and Lunsford (1990) identify a large number of strategies that have been used in collaborative writing. A shared workspace is provided in some computer systems to help the convergence of collaboration in small groups (Chen & Rada, 1995; Whittaker, Geelhoed, & Robinson, 1993). Coauthors can communicate with each other through a shared workspace as well as communicate directly with each other (Miles, McCarthy, Dix, Harrison, & Monk, 1993). Olson, Olson, Storrosten, and Carter (1993b) compared groups of designers using a shared editor called *ShrEdit* with groups who worked with conventional whiteboard, paper, and pencil. The *ShrEdit* tool helped the supported groups focus on key issues in the design and avoid spending more time on less important topics. The groups working with *ShrEdit* generated fewer but better design ideas. Coauthoring systems requiring explicitly specified roles have been found inflexible to deal with the complex and dynamic nature of the most informal collaborative writing (Fish, Kraut, Leland, & Cohen, 1988).

The MUCH System

The Multiple Users Creating Hypermedia (MUCH) system has been developed for collaborative authoring of research papers, knowledge sharing, and electronic publishing. A series of versions of the MUCH system have been implemented on Hewlett Packard UNIX graphical workstations. The latest one was developed with the Andrew Development Toolkit (ATK). The Andrew version provides a What-You-See-Is-What-You-Get (WYSIWYG) user interface. Chen, Rada, and Zeb (1994) developed a model of collaborative writing with the MUCH system, and the empirical evidence in their study led to some insights into the use of the MUCH system as an evolving, shared workspace for collaborative writing. Readers are referred to Zheng & Rada (1994) for technical details regarding the design of the MUCH system.

The user interface of the MUCH system consists of an *outline* window and a *content* window. The outline window displays an outline of the hypertext, which is generated by a graph traversal algorithm. The content window shows the content of the current node selected through the outline window. The MUCH system provides a set of functions in its user interface for various tasks, such as manipulating the underlying semantic-network and editing the contents of nodes. These functions form a framework for users to interact with the collaborative hypertext. The main functions in the MUCH user interface include:

- Unfold—This operation is always based on a selected entry in the outline. As the outline is unfolded, new entries at a lower level are inserted to the existing outline according to a one-step forward breadth-first traversal algorithm for nodes that are linked to the selected node;
- Read—This operation displays the content of the selected entry in the outline;
- Lock—The operation applies a lock to the content of the current node. If the operation is successful, the content is protected from other users until the lock is released. However, the content of a locked node is readable to concurrent users;
- Info—This operation displays statistical information regarding the current node; and
- Update—This operation saves the updated content to the underlying database.

Valuable experiences and lessons have been learned from collaborative writing and related work with the MUCH system (Chen et al., 1994). However, the nature of collaborative writing and how it can be effectively supported by computing technologies are yet to be fully understood (Sharples et al., 1993). A clear understanding of the structure of interactive behaviors is necessary to gain further insights into the interrelationship between the work and the technology.

Modeling Interactive Behaviors in Collaborative Work

Modeling interactive behaviors in computer supported collaborative work is a new area. Researchers are brining into this area a variety of modeling techniques. On the other hand, there is a need for a systematic, flexible, and powerful approach to the analysis and modeling of computer supported collaborative writing.

Researchers have recognized that a descriptive–prescriptive approach to the analysis and modeling of computer supported cooperative work has a number of significant potentials. For instance, the heuristic power of a descriptive–prescriptive model may lead to an integration of a formative approach to the mainstream of software engineering. Automated protocol analysis and modeling can provide the information needed for simulating, visualizing, and monitoring an interactive process in real-time (Smith, Smith, & Kupstas, 1993). A descriptive–prescriptive approach is appropriate for investigators to deal with both the dynamic nature of computer supported collaborative writing and the formal aspects that are needed to incorporate the analytic and inferencing power into the practice of software engineering.

Protocol Analysis

Siochi and Hix (1991) analyzed behavioral sequences of maximally repeating patterns for heuristic evaluation of user interfaces. They reasoned that, if a particular behavioral pattern occurred repeatedly, then the pattern could reveal two types of underlying relation between users and the computer interface. The pattern may indicate an intrinsic connection of several functions and these closely related functions can be integrated so as to fit smoothly into users' workflow. Alternatively, the pattern may indicate a problem of human–computer interaction. This technique is found useful in uncovering design problems with various interfaces.

Smith et al. (1993) studied the strategies used by professional writers with a hypertext writing system *Writing Environment* (WE). As writers used WE, their behavior was automatically captured in time-stamped logs. These logs contained the actions performed by users and the context in which an action took place. The logs were analyzed with a cognitive grammar and the sequences of interactive behaviors were classified into various high-level coding categories. The high-level coded behaviors represent classes of mental activities as defined by a cognitive theory of writing. The planning strategies of these writers were analyzed by Lansman, Smith, and Weber (1993) based on statistical characteristics of these sequences.

Smith et al. (1993) developed a set of tools which can *replay* the interaction between a user and a writing support system for automated protocol analysis. These tools track user behavior and produce a machine-recorded protocol. In addition, users' strategies can be modeled in formal cognitive grammars. Smith, Weiss, and Ferguson (1987) emphasized methodological merits of their approach to the analysis of writing strategies with computer systems.

The goal of this study is to capture the essence of interactive behaviors of users with a collaborative hypertext system. This study concentrates on interactive behaviors obtained through a built-in data collection process in the collaborative authoring system.

Markov Chain Models

A behavioral pattern is a recurring sequence of interactive behaviors of users with a computer system. These patterns may reveal valuable insight into the dynamics of collaborative writing. Traditional transaction analysis of search patterns with interactive systems is an efficient way to understand an ongoing process with the least interference to the work. Previous studies mainly focused on information retrieval patterns in a static information space, i.e., there are few changes in the structure of the information space. In contrast, tasks such as local composition, structure organizing, navigating, and searching are all related to collaborative writing. In this study, a stochastic modeling approach is used to analyze the behavioral structure of collaborative writing with the MUCH.

By using stochastic modeling techniques, researchers may derive compact views on the nature of collaborative writing. There is great potential of automating such approaches for wider application. The method can be applied to the study of the use of larger, distributed collaborative systems (Bishop, Fienberg, & Holland, 1975). Few studies have addressed the application of stochastic modeling techniques in CSCW and even fewer in computer supported collaborative writing. One reason perhaps is that the application of these techniques requires some degree of expertise in stochastic processes. Another reason perhaps is that to apply these techniques, a large amount of empirical data are needed and this amount of data are not usually available due to the fact that collaborative writing systems are still in a formative stage.

Occurrences of interactive events in collaborative writing with the MUCH system are conceptualized as a stochastic process. Many significant issues can be addressed in such stochastic models, in particular, Markov models, for example,

- What is an appropriate state space for describing the structure of collaborative writing?
- How can this state space be derived from empirical data?
- How can a Markov model capture the dynamic nature of collaborative writing?
- Are these Markov models affected by time? Do these Markov chains settle down to a unique probability distribution of the state space?
- Can a state space be decomposed into some smaller and independent state spaces so that researchers can narrow down their focus to specific aspects of collaborative writing at a time?

These questions have profound implications for understanding the dynamics of collaborative writing and for integrating several existing methodologies as a novel, efficient approach to the study of highly dynamic, complex work such as collaborative writing. The descriptive–prescriptive nature of the approach allows investigators to formalize their research hypotheses on specific aspects of interactive behaviors in collaborative writing and refine these models with a close connection to the reality.

Markov chain models have been used to study online database search and behaviors related to other interactive systems (Chapman, 1981; Penniman, 1975; Qiu, 1993; Tolle & Hah, 1985). Penniman (1975) found that individuals developed complex and unique behavioral patterns in online search and that the complexity may require at least a second-order Markov chain to capture. Qiu (1993) analyzed information search patterns with a Hyperties™-based hypertext system and formally verified that these patterns are characterized by a second-order Markov chain.

Collaborative writing, at least, can be as dynamic and complex as searching an interactive information system. Based on existing findings with interactive systems such as online bibliographic databases and earlier hypertext systems, this study hypothesizes that the sequential structure of collaborative writing behaviors with the MUCH system can be modeled by a second-order Markov chain.

Once the appropriate model is established, behavioral patterns in collaborative writing are examined based on the descriptive–predictive second-order Markov model. Models for users with different levels of experience with the MUCH system are compared on the hypothesis that they represent behavioral patterns of different nature. Furthermore, models for collaborative writing in independent project workspaces are compared to investigate the effect of a workspace as a whole on the organization of collaborative writing. The study also addresses some particular issues, such as frequently used functions of the MUCH system, how these functions are related to one another in collaborative writing, and implications of the identified sequential structure for collaborative writing and the design of computer systems.

Method

This study takes a descriptive–prescriptive approach. The modeling work in this study is based on Markov analysis. The mathematical treatment of Markov models can be found in the literature of probability and mathematical statistics (e.g., Bishop et al., 1975). State transition probabilities are empirically estimated based on observed time series data of interactive behaviors in collaborative writing with the MUCH system. Three hypotheses regarding the resultant Markov chain models are tested. Graphical representations are provided to illustrate the results of the investigation.

Data Collection

Interactive behaviors of collaborative writing with the MUCH system were logged for 3 months on seven active databases. Each interactive event was recorded with the name of the function involved at the user interface, the starting time of the event, and the heading of the activated node so that the event is associated with a unique point in the collaborative hypertext. The semantics of operating a function and implications of the event in collaborative writing are associated by temporal and spatial characteristics.

The sample of interactive behaviors was drawn from a pool of more than 20,000 events for each collaborative hypertext by 24-hour recording over 3 calendar months in 1994. The usage of the MUCH system appeared to peak in certain hours in working days. A time window from 8:00 a.m. to 18:00 p.m. was imposed on sequences of interactive behaviors for subsequent analysis. Data on Saturday and Sunday were excluded. The resultant models are based on the data from normal working hours in weekdays.

An initial state space with six states—constructing, browsing, reading, awareness, writing, and printing—was derived based on 24 distinct types of events observed in the MUCH system. The recording of transactions was announced at the beginning of each session with the MUCH system and the consent of individual users was obtained for the analysis of these data.

User and Task

There were two types of users involved in collaborative writing during the period of observation. A research group included researchers, visiting academics, and research students, whereas a student group consisted of graduate students enrolled in an M.Sc. course in Information Systems at the University of Liverpool.

Users were involved in drafting and editing several coauthored manuscripts as research papers and textbooks. The MUCH system was used as a workstation-based word processor as well as a network organizer. Writing tasks, for instance, were divided into smaller tasks, such as writing and organizing a number of hypertext nodes. Collaboration was based on the shared workspace among coauthors.

Students formed seven 3-person groups to write a joint group essay on groupware technologies. Two weeks were allowed for the collaborative writing. The members of a group were required to produce individual reports to describe the collaboration from their own views and whether they are satisfied with the work. The group essay was written into the MUCH system, whereas individual reports were E-mailed to the author directly. According to these individual reports, the following tasks were involved in their group writing:

- Background reading and initial planning;
- discussing and choosing a topic for the group essay, and generating an outline;
- drafting the essay directly in the MUCH system;
- editing the draft by one member of the group;
- revising the work by the group; and
- submitting the essay.

In the analysis, users were divided into two groups according to the total number of transactions made by each user during the period of observation. Two natural clusters emerged in terms of the total number of transactions. The total number of transactions of an active, regular user of the MUCH system ranges from 1,500 to 9,000. For an infrequent, occasional user, the figure is less than 1,000. Regular users are likely to have established strategies of collaborative writing with the MUCH system, whereas occasional users may only have underdeveloped strategies and behavioral patterns. In addition, collaborative hypertext as a whole, including structure and content, may influence the sequential structure of interactive behaviors in collaborative writing. This impact is explored by classifying the underlying databases according to the similarities in behavioral patterns as described by corresponding Markov chain models.

The behavior of each individual user of the MUCH system was recorded in separate files. A state transition matrix was generated for each user based on the data. Individual transition matrices were aggregated and the mean of corresponding transition probabilities of all the individual users in a group were used as the grand transition probabilities for the group.

The above sequence of 22 events was observed over a 10-minute session on the MUCH system. This sequence is used to illustrate the procedure of modeling. Five types of events appeared in this short session: (A) Unfold, (B) Read, (C) Lock, (D) Update, and (E) Quit. The session can be coded as follows:

AAABCDBCDBCDBCDBCDBCDE.

The occurrence count shows 3 As, 6 Bs, 6 Cs, 6 Ds, and 1 E in the sequence. The sequence can be represented by a transition matrix such that each element in the matrix represents the frequencies of a transition from one state to another between time points t and $t + 1$. For example, sequence ABCDB contains the following transitions: A $\rightarrow$ B, B $\rightarrow$ C, C $\rightarrow$ D, and D $\rightarrow$ B. Assuming once the process is in state E, it will never leave the state E, the following matrix represents the frequencies of all the possible transitions in the session.

TABLE 1. A sequence of interactional events with the MUCH system.

Time	Event	Target node of the transaction
14:39:30	Unfold	Courseware development coordination and reuse
14:39:32	Unfold	University examples
14:39:36	Unfold	MITs Athena project
14:40:23	Read	University examples
14:40:39	Lock	University examples
14:41:33	Update	University examples
14:41:43	Read	MITs Athena project
14:42:06	Lock	MITs Athena project
14:42:37	Update	MITs Athena project
14:42:41	Read	TUDOR
14:42:58	Lock	TUDOR
14:43:27	Update	TUDOR
14:43:33	Read	Physical geography tutor
14:43:49	Lock	Physical geography tutor
14:44:52	Update	Physical geography tutor
14:44:59	Read	Purdues escape
14:45:11	Lock	Purdues escape
14:45:37	Update	Purdues escape
14:45:49	Read	Organizational issues
14:46:40	Lock	Organizational issues
14:47:43	Update	Organizational issues
14:49:09	Quit	Organizational issues

	A	B	C	D	E	Row sum	Probability distribution
A	2	1	0	0	0	3	.14
B	0	0	6	0	0	6	.27
C	0	0	0	6	0	6	.27
D	0	5	0	0	1	6	.27
E	0	0	0	0	1	1	.05
						22	1.00

The column of row sums is normalized over the total number of events occurred. The resultant vector is the probability distribution of the 5 states. The probability of state i is denoted as $p(i)$, $i = 1, 2, 3, 4, 5$. The vector for this example is shown as the right column in the table.

The 5 by 5 matrix of transition frequencies can be similarly normalized by dividing each of its row frequencies by the respective row sum. The elements of the resultant matrix P are called sequential or transitional probabilities. The element (i, j) in the matrix P is the probability of being in the state j at time $t + l$ given that the process is in the state i at time t. The matrix below results from the normalization of the 5 state session. The i-th row of the matrix is now a probability distribution of the possible outcomes of a transition from state i.

$$P = \begin{bmatrix} 2/3 & 1/3 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 5/6 & 0 & 0 & 1/6 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Markov chain analysis is the first step of a process modeling. The behavior of a Markov chain can be described in several types of states, including absorbing states, transient states, recurring states, and ergodic states. Markov chain analysis often addresses issues such as estimating the transition matrix from empirical data, the stationarity of a stochastic process, the appropriate order of the chain, and identifying transient and persistent states. Once the transition matrix is obtained, one could use various existing techniques of Markov analysis to study the homogeneity of the distribution of the probabilities, the symmetry of the transition matrix, the distribution of the process in a long-run, and the difference of the matrices under different experimental conditions.

Analysis and Modeling

This study focuses on the most salient behavioral states in collaborative writing with the MUCH system and how users move from one state to another as the process evolves. *Statistical Package for the Social Sciences* (SPSS) is used for the analysis. Markov models were specified in terms of hierarchical log-linear models in SPSS.

Log-linear and Markov models. The concept of Markov chain models is based on a state space of stochastic variables and transitions from one state to another. If the state of a stochastic process at time t depends on the previous r states at the time points $t - 1, t - 2, \ldots, t - r$, where $r \geq 1$, then the process is called an rth-order Markovian process. The following definitions and notations are provided for the discussion purpose of the article. Using log-linear models for Markov analysis is described in Bishop et al. (1975).

The set of distinct values taken by a stochastic process is called the state space of the process. For a finite or countable state space S, a stochastic process defined on the space is called a chain. The Markov property is defined as follows, for a stochastic process $\{X_t\}$ and all the states $s_t \in S$, $t = 1, 2, \ldots,$ the following equation is true:

$$P[X_t = s_t | X_{t-1} = s_{t-1}, X_{t-2} = s_{t-2}, \ldots, X_1 = s_1] = P[X_t = s_t | X_{t-1} = s_{t-1}].$$

The most important property of a first-order Markov model is that, given a state at time t, the state at time $t + 1$ becomes independent of earlier states at time $t - 1$, $t - 2$, and so on. A discrete-time Markov chain is stationary or homogeneous in time if the probability of going from one state to another is independent of the time when an event takes place. The *transition probability* from i to j in a stochastic process is defined as the conditional probability $p_{ij} = P[E_j | E_i]$, where E_i and E_j are usually some observable events. Transition probabilities can be arranged as a matrix of probabilities and the value at the cell (i, j) is p_{ij}. This matrix is called the *transition probability matrix* associated with the discrete-time stationary Markov chain $\{X_t\}$.

A transition matrix has two properties: 1) All the cells in the matrix have non-negative values, and 2) the total of each row is one. The transition matrix contains all the information needed to describe the motion of the chain among the states in S. The starting position of a chain is represented by a vector $a_0 = (\alpha_1, \alpha_2, \ldots, \alpha_n)$ which satisfies $\Sigma_i \alpha_i = 1$ and $\alpha_i \geq 0$ for $i = 1, 2, \ldots, n$. The starting vector gives a probability distribution. If P denotes the transition matrix, the distribution of where the process is after n steps is given by $a_n = a_0 P^n$, where P^n is a transition matrix that represents the n-step-transition probabilities.

The transition probability matrices are estimated from the observed counts of each event recorded by computer logs. Log-linear models have been increasingly used by researchers over the recent decade as a powerful tool to analyze categorical data sets. Log-linear models are used to compute expected counts according to the structure characterized by the model.

The observed two-step transitions can be arranged as a contingency table. The value of the cell (i, j) in the table is the count of observed transitions from state i to state j. A second-order Markov chain models the counts in a three-dimension contingency table. The expected value x_{ijk} of the cell (i, j, k) in the table is predicted by the general log-linear model (Bishop et al., 1975, p. 269) in Equation 1. The term u is the grand mean of the logarithm of the observed counts across the contingency table, the term $u_{1(i)}$ is the mean of the logarithm for the ith row of the variable 1. The term represents the deviation from the grand mean under the impact of the ith level of the categorical variable 1.

Equation 1. Log-linear model for a second-order Markov chain.

$$\ln(x_{ijk}) = u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{12(ij)} + u_{13(ik)} + \mathrm{u}_{23(jk)} + u_{123(ijk)}.$$

If the process can be modeled by a first-order Markov chain, all the second- and higher-order terms will not present in the model and the model is reduced to Equation 2.

Equation 2. Log-linear model for a first-order Markov chain. $u_{123} = 0$ and $u_{13} = 0$.

$$\ln(x_{ijk}) = u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{12(ij)} + u_{23(jk)}.$$

Note that the term $u_{123(ijk)}$ and $u_{13(ik)}$ correspond to the second-order effects, therefore they do not appear in the equation that specifies a first-order Markov chain. In the cases of a first-order Markov chain, the term corresponds to the effect of a starting state i and the term $u_{2(j)}$ corresponds to an ending state j.

The order of a Markov chain is determined by log-linear models corresponding to a range of Markov chains with various order. A kth-order Markov model can be verified if the k-way interaction is necessary for an adequate fit for the data and removing a $(k + 1)$-way interaction from a corresponding log-linear model does not affect the fitness of the model. In general, Pearson's goodness-of-fit chi-square statistic is recommended for its relatively stable approximate to the χ^2 distribution with small sample sizes (Fienberg, 1980).

Markov models of the third- or lower order are examined to determine the appropriate order of the Markov chains. Previous research has shown that search patterns with online information systems can be adequately modeled by a second-order Markov chain (e.g., Qiu, 1993). The results of this analysis provide a baseline for subsequent analyses of user behavior with collaborative hypertext.

Three major hypotheses were formalized as follows:

- *Hypothesis 1:* The sequence of interactive behaviors of users working with the MUCH system can be adequately represented by a second-order Markov chain.
- *Hypothesis 2:* Regular users and occasional users employ significantly different strategies in interacting with the MUCH system. This hypothesis focuses on the effects of users' experience with the MUCH system and knowledge of these databases on the sequential structure.
- *Hypothesis 3:* Interactive behaviors of regular users are significantly affected by the context provided by the underlying database. The similarities among Markov models over different databases are measured by partial likelihood ratio chi-square statistics.

In addition to testing these hypotheses, this study particularly examines first-order Markov chain models to reveal the significance of sequential characteristics of user behaviors. The patterns in first-order chains are preserved in higher-order chains (Penniman, 1975; Qiu, 1993). The simplicity of first-order chains can be very useful for understanding of the patterns in higher-order chains.

Hypothesis 1. Hypothesis 1 on Markov models was formulated in terms of hierarchical log-linear models in a four-way cross-tabulation of state variables (Bishop et al., 1957; Norusis, 1985). This contingency table corresponds to a third-order Markov chain. The value m_{ijkl} of a cell (i, j, k, l) is the observed frequency of a four-way interaction $S_1^i S_2^j S_3^k S_4^l$, where i, j, k, and l are the levels of categorical variables S_1, S_2, S_3, and S_4. This four-way interaction corresponds to a three-step transition $S_1(i) \rightarrow S_2(j) \rightarrow S_3(k) \rightarrow S_4(l)$. A log-linear model partitions the effects of the levels as well as the categories on the logarithm of the count, $\log(m_{ijkl})$, for each cell. The following hierarchical log-linear model specifies a second-order Markov process:

Saturated log-linear model:
(H1.1) $\{S_1^* S_2^* S_3^* S_4\}$
Two-step transition model:
(H1.2) $\{S_1^* S_2^* S_3\}\ \{S_2^* S_3^* S_4\}$

where $\{S_1S_2S_3\}$ and $\{S_2S_3S_4\}$ are the generating class for the hierarchical log-linear model. On the other hand, $S_1S_3S_4$ means the individual's states at the time points t_3 and t_4 still depend on the state at the time point t_1, which in effect specifies a third-order Markov chain and therefore should not be included in the second-order Markov model. If the model (H1.2) represents the dataset adequately, the chain is at the most second-order. If the model (H1.2) is inadequate, then the chain is at least third-order.

The analysis included several structural zeros determined on an empirical ground. Defining structural zeros imposes additional restrictions on the behavioral patterns. SPSS log-linear models treat the observed zeros as sampling zeros unless the cells are specified with structural zeros. Structural zeros were only imposed on the structure of the transition matrices if both theoretical and empirical points of view suggested as necessary.

Hypothesis 2. This hypothesis is concerned with the effects of users' overall experiences with the MUCH system. Users are divided into two groups for regular users who used the seven databases regularly and for occasional users who only use these databases sporadically. A user is classified as an occasional user if he or she engaged in less than 1,000 interactive events, whereas a regular user engaged in at least 1,500 events over the period of observation. Once it is known that the underlying process of interaction is a second-order Markov chain, one can test whether two Markov chains are significantly different for the two groups of users.

The following log-linear model tests the hypothesis on a $2 \times 7 \times 6 \times 6 \times 6 \times 6$ cross-tabulation for both user groups, i.e., USER $\times$ DATABASE $\times$ CHAIN.

Saturated log-linear model:
(H2.1) $\{S_1^* S_2^* S_3^* S_4^* \text{USER}\}$
Effect of users' experience:
(H2.2) $\{S_1^* S_2^* S_3^* \text{USER}\}\ \{S_2^* S_3^* S_4^* \text{USER}\}$

The user differences correspond to a two-level USER variable (1 = regular users, 2 = occasional users). The categorical variable DATABASE has 7 levels for the seven databases from the most collaboratively used to the least collaboratively used one. Given that the process is a second-order Markov chain, if the model (H2.2) fits the data well, then it is evidence that the effect of users' experiences is significant to the second-order chain.

Hypothesis 3. Hypothesis 3 states that the database will have a significant overall impact on regular users' behavioral patterns. Behavioral patterns of these users will vary from database to database. The structure of the usage patterns is related to a set of characteristics of the database being used. This hypothesis can be tested with log-linear methods on the same cross-tabulation described in the previous section.

Saturated log-linear model:
(H3.1) $\{S_1^* S_2^* S_3^* \text{DATABASE}^*(\text{USER} = 1)\}$
Effect of databases on behavioral patterns:
(H3.2) $\{S_1^* S_2^* S_3\}$

If the model (H3.2) fits the dataset adequately, then the process is a second-order Markov chain, regardless the differences in databases or users. This test also identified the similarities among databases in terms of associated behavioral patterns. The similarity was measured by the likelihood ratio chi-square statistic. These chi-square values measured pairwise similarities of the seven databases. The similarities were scaled to distances among databases by multi-dimensional scaling techniques.

A deep understanding of the state transition patterns will contribute to the understanding of collaborative writing with a shared information space; what do the people do to organize their work in a collaborating group, and what types of computer support are appropriate for these tasks? In this study, the behavioral patterns refer to stochastic regularities that have emerged from interactions between users and the MUCH system.

Aggregated state space. The MUCH system supports more than 20 types of transaction from its user interface. Some of them have been used frequently, while some have only been used occasionally. One technique which has been used in Markov chain analysis and log-linear models is to lump closely related states into a new, summarizing state such that the original state space can be replaced with a smaller state space without losing much information (e.g., Olson et al., 1994; Qui, 1993). As a result, there will be fewer sampling zeros in the new transition matrix. Log-linear models based on the aggregated state variables are expected to have a better goodness-of-fit statistics.

Each aggregated state variable consists of individual transaction events which characterize particular modalities of collaborative writing with shared hypertext databases. Intermodality transitions are described by corresponding state transitions in the new state space. Combining state variables to form a new state space assumes that the individual state variables in the original state space can be classified into groups such that transition probabilities from state variables in one group to the state variables in another group are generally similar. Such groupwise homogeneity of transition probabilities are normally assumed without further investigation. In this research, state variables are classified into four groups according to the following criteria:

- Goal of the interactive action: Browsing/authoring;
- Scope of the interactive action: Local/global;
- Impact on concurrent users: Transient/persistent;
- Target object on which the function acts: Agent/artifact.

These criteria result in four types of transaction events, which form a new state space and each random variable in the space can have one of the four states. Transaction events are mapped to one of the types exclusively and exhaustively as follows:

- Local content: Authoring, local, transient/persistent, artifact;
- Global structure: Authoring, global, persistent, artifact;
- Global view: Browsing/authoring, global, transient, artifact;
- Awareness: Browsing/authoring, local, transient, agent.

In addition, transaction events are classified with reference to the implementation of the MUCH system. In particular, the user interface of the MUCH system is mainly based on two windows, one containing an overview to the database organization and the other containing the content of the focal node. Most global transaction events take place in the overview window, whereas local transaction events are concentrated to the content window. Transaction events related to awareness seeking may take place in either window.

Results

The major results of the Markov analysis indicate that the dynamic nature of collaborative writing with the MUCH system can be captured by a second-order Markov chain, the structure is affected by users' experience with the system, and the structure is also affected by substantive characteristics of collaborative writing tasks. First-order state transitions revealed some interesting patterns which may lead to a useful partition of the state space. It becomes clear from the structure of these patterns that the MUCH system was intensively used for exploring, organizing, and outlining tasks, whereas most collaboration facilities in the MUCH systems were used with a transient nature. There appears to be a strong tendency for users to return to the former mode of interaction.

Process Structure

The first hypothesis concerns the extent to which direct manipulation events of users are interrelated. Log-linear tests showed that an interactive process with the MUCH system is a second-order Markov chain. The process can be adequately modeled by a second-order Markov chain (Pearson's $\chi^2 = 660.86$, $df = 780$, $p = 0.9992$), but not by first-order Markov chains ($\chi^2 = 6523$, $df = 102$, $p < .0001$). The tests were based on transactions from both regular and occasional users, i.e., experienced and inexperienced users.

Most recurrently second-order transitions from regular users were dominated by Browsing (B), Reading (R), and Writing (W). Log-linear models suggest that, in essence, an interactive process (IP) has the following structure:

$$B^p = B \to B \to \cdots \to B, \ (p - 1 \text{ times})$$

$$IP = B^p \to (R^q \to W^r)^s \to IP,$$

$$p, q, r, s = 1, 2, 3, \cdots$$

A Structuring state tends to be followed by a Browsing state. Users adjust their views to a shared workspace as the organization of the workspace changes. The model indicates using a shared workspace not only involves searching and browsing, but also includes writing and organizing.

Effects of Users' Experience

It has been expected that an interactive process with the MUCH system would be affected by the level of users' experience with the system. Users were divided into two groups, one for experienced users and one for inexperienced users, according to the number of transactions conducted over the 3-month period of time. Hypothesis 2 is stated in the null form, that the patterns of users in the two groups do not significantly differ when they use the same database.

A log-linear model was used to compare the second-order Markov chains between the two groups of users with the database *Groupware and Hypermedia.* The second-order Markov chains for active users and inactive users are significantly different (Pearson' $\chi^2 = 2298.35$, $df = 28$, $p < .001$). The first-order transition probability matrices were examined to find where the patterns of these users differ as the differences in first-order transitions will be persistent in second- and higher-order chains. Differences of behavioral patterns between active users and inactive users were also found with the *managerial* database ($\chi^2 = 66552.86$, $df = 22$, $p < .001$). The null hypothesis was rejected and the level of users' experience has significant effects on the transition patterns they use.

Log-linear tests, based on the use of seven hypertext databases, found the Markov chains of regular and occasional users are significantly different (Pearson's $\chi^2 = 5880.91$, $df = 180$, $p < .001$). Differences between the two groups were specified by corresponding λ parameters in log-linear models.

The scope of a Browsing state is within the overall organization of the hypertext database, the scope of Writing is limited to the content of a focal node, and the focus of Reading state moves from organizational structure to detailed, local information.

- Highly used *R-R-B* transitions by regular users ($Z = 4.17$) suggested that they frequently adjust the focus and scope of their views. They browse the organizational structure more extensively than occasional users.
- The pattern of *R-A-R* ($Z = 2.57$) indicates that, as users read the content of a shared workspace, they pay more attention to social-construction aspects of the workspace than occasional users.
- *A-R-B* ($Z = 2.48$) and *A-R-W* ($Z = 2.23$) implied regular users require the awareness of collaborative authoring at both the organizational and content level of the workspace.

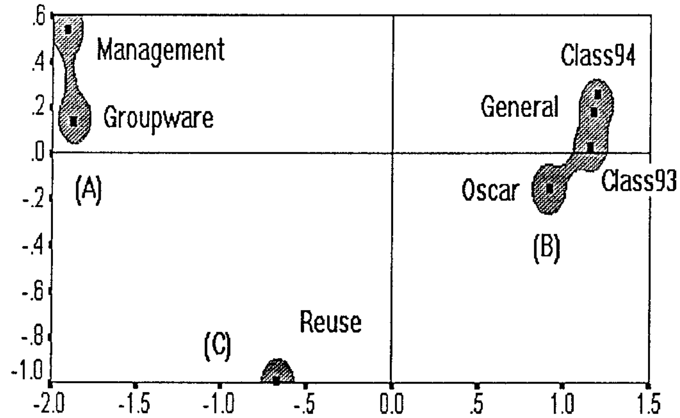

FIG. 1 Classification of hypertext databases according to the similarity of corresponding Markov chains (stress = 0.0386, RSQ = 0.9950).

Effects of Underlying Hypertext Databases

The third hypothesis speculates that user behavior depends on the structure and contents of underlying databases, even though they use the same user interface. The organization and content of an information space significantly affects the way that it is used. The influence was compared between the processes from two workspaces (Pearson's $\chi^2 = 19052.12$, $df = 1296$, $p < 0.001$).

Databases were grouped into three clusters by the similarity of associated processes. Second-order transitions were aggregated in each cluster to characterize user behavior which corresponds to the three clusters of workspaces. Cluster A includes the Management and Groupware databases; Cluster B includes the General database, a database for a joint project, and databases for students in classes; and Cluster C contains the software reuse database. The examination of log-linear models shows significant differences in patterns of user behavior associated with these clusters (Fig. 1).

Cluster A.

Patterns such as $R \rightarrow A \rightarrow B$ and $W \rightarrow A \rightarrow B$ were predominant ($Z = 2.52$ and $Z = 1.96$, respectively). Users seek social awareness before they transit from the content level to the organizational level of the shared workspace. Awareness seeking appears as a local activity.

Cluster B.

The pattern $R \rightarrow B \rightarrow B$ ($Z = 2.79$) characterizes the behavior of an occasional user with general tasks and the pattern $R \rightarrow W \rightarrow B$ ($Z = 2.34$) suggests the focus of an interactive process alternates between the organizational and content level of a shared workspace. The $R \rightarrow X \rightarrow A$ patterns in Cluster B suggest that the stability alone

TABLE 2. Summary table of the activity of individual users.*

Analysis	Subject no.	Transactions	Valid frequencies
Included	S9	6,953	57.5
	S8	4,126	34.1
	S7	374	3.1
	S6	280	2.3
	S10	217	1.8
	S1	98	.8
	S5	28	.2
Excluded	S11	4	.0
	S2	3	.0
	S3	3	.0
	S4	3	.0
Total		12,089	100.0

* Users whose transactions count less than <1.0% are omitted from entering into the sample.

may not explain the awareness needs which arise in the process of interaction with the workspace.

Cluster C.

The patterns of $W \to W \to B$ ($Z = 3.17$) and $R \to W \to B$ ($Z = 2.06$) were found. These patterns highlight an independent working mode in writing with a hypertext system. The lack of these patterns in Cluster A indicate that those processes have more complicated structures because of the complexity of the organization and evolution of these workspaces. Processes of Cluster C also have patterns of $X \to B \to C$, indicating an extensive evolution of the shared database.
Influential factors on browsing and awareness-seeking behavior are summarized as follows:

- Users expand and adjust the contextual views frequently to a rapid changing shared workspace. Social awareness is required at both the organizational and content level. The heterogeneity of the information exchanged in the workspace and the commitment of the collaborating team significantly influence the patterns.
- Social awareness needs did not stand out in interactive processes associated with a stable workspace. These processes basically correspond to independent writing modes. Changes in the workspace do not specifically increase awareness requests.

Patterns in one-step transitions.

The transition matrices from the use of three databases are presented, including *Groupware & Hypermedia*, *Class*, and *Management* databases. The three databases are selected because they have been evolving most intensively among the seven databases observed. They reflect different aspects of the dynamics of collaboratively using the MUCH system in terms of a collaborative learning environment, a collaborative writing environment, and an organizational memory. First, to illustrate some interesting details of user behavioral patterns, the usage and behavioral models for the *Groupware & Hypermedia* database are introduced in detail. Then, behavioral patterns are discussed based on a simplified state space for the stochastic process.

TABLE 3. Interactions with the *Groupware & Hypermedia* database.

Analysis	Transaction	Occurrences	Percentage
Included	Unfold	4,383	36.3
	Read	3,136	25.9
	Lock	1,301	10.8
	Fold	1,210	10.0
	Update	1,188	9.8
	Delete	184	1.5
	Quit	174	1.4
	Modify	150	1.2
	Info	90	.7
	Rename	84	.7
	Save	66	.5
	Create note	63	.5
	Send	20	.2
	Refresh	15	.1
	Word	8	.1
Excluded	Preview	4	.0
	Print	4	.0
	Users	3	.0
	Check	2	.0
	Make outline	2	.0
	Author	1	.0
	Browser	1	.0
	Total	12,089	100.0

The *Groupware & Hypermedia* database. The computer logs recorded transactions from 11 users over the 3-month period of observation (see Table 2). Some users accessed the database with short and isolated sessions, for example, for printing a document stored in the hypertext space (valid frequencies < 1.0%). The behavior of these users has limited representative power to our study; the transactions made by these users were removed from further analysis.

The percentage breakdowns of user behavior revealed some interesting characteristics about the occurrences of particular types of event (see Table 3). The most frequently occurred transactions are Unfold, Read, Local,

TABLE 4. Time band and transactions.

Time band	Transaction	Percentage	Cumulative
Before 7:00 a.m.	151	1.3	1.3
8:00–13:59	6,043	50.0	51.3
14:00–16:59	3,827	31.7	83.0
17:00–22:00	1,402	11.6	94.6
After 22:00 p.m.	651	5.4	100.0

TABLE 5. The transition probability matrix of the first order 13-state Markov chain.

	UNF 19	RED 14	LOK 9	FLD 6	UPD 20	DEL 5	MD 10	INF 8	REN 16	SAV 17	SND 18	FRS 15	QIT 13
19	.686	.164	.012	.120	.006	.003	.001	.001	.000	.000	.000	.001	.004
14	.088	.458	.283	.041	.005	.035	.034	.015	.017	.013	.002	.001	.009
9	.030	.056	.215	.012	.666	.000	.000	.005	.030	.010	.001	.000	.011
6	.465	.140	.005	.362	.005	.002	.002	.000	.001	.002	.000	.004	.012
20	.061	.541	.056	.078	.218	.001	.003	.003	.001	.003	.002	.000	.026
5	.628	.022	0.00	.005	.000	.339	.005	.000	.000	.000	.000	.000	.000
10	.773	.002	0.00	.007	.000	.000	.200	.000	.000	.000	.000	.000	.000
8	.101	.326	.056	.067	.067	.000	.000	.315	.011	.000	.000	.000	.056
16	.759	.000	.060	.012	.000	.000	.000	.000	.133	.000	.000	.000	.036
17	.108	.262	.046	.031	.000	.000	.000	.000	.000	.231	.000	.000	.323
18	.006	.404	0.00	.000	.006	.000	.058	.000	.000	.000	.520	.000	.006
15	.286	.239	0.00	.000	.000	.000	.000	.000	.000	.000	.000	.475	.000
13	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	1.00

Fold, and Update. The occurrences of these actions are at least 10 times more than the rest of the actions.

The spectrum of frequency from the duration between two adjacent events shows that 95.8% of interactions took place with the 5-minute intervals, whereas only 1.1% of interactions are separated by an interval which is longer than an hour. Table 4 shows how the *Groupware & Hypermedia* database had been used throughout a day in terms of the frequencies of transactions. The database appeared to be used more in the morning than in the afternoon. The number of transactions was also calculated for each working day. There is no apparent pattern except the off-peak period on Saturday and Sunday.

A full-scale 13-state transition probability matrix for the *Groupware & Hypermedia* database is given in Table 5. The transition matrix indicates two types of interactive events between users and the system. The central Type I interactions include Unfold (UNF), Read (RED), Lock (Lok), Fold (FLD), and Update (UPD). All the events in this group communicate each other. The auxiliary Type II interactions are transient in that users usually do not move within in the group in an adjacent step. Instead, the process is likely to return to Type I behaviors. This pattern is shown in Table 5: In the upper left sub-matrix all the transition probabilities are positive, but in the lower right sub-matrix the non-reflexive transition probabilities are essentially zero.

Table 6 shows the one-step 4-state transition probability matrix derived from the use of the *Groupware & Hypermedia* database. The matrix indicates a similar pattern of changing from one mode to another. Users are much more likely to move into states such as Local Content and Global View. The probability that a one-step transition lands in these two states is .954 (.501 + .453), while the probability of landing into the other two states is .046 (.009 + .037).

As shown in Figure 2, the emerged patterns of interactive behaviors of users with the *Groupware & Hypermedia* database reveal that users either persistently worked in one of the four modes with the MUCH system, or they moved from social, contextual modes to independent working modes. A filter of transition probabilities is set at the level of $p > .05$ in the diagram. The influence of the technological design of the MUCH system on the independent working modes is evident in terms of an interactive semantic work for exploring ideas for writing and an editing window to support writing at the level of local composition.

TABLE 6. *Groupware & Hypermedia* database: One-step combined transition matrix.

One-step transition	Local content (LC)	Global view (GV)	Group awareness (AW)	Global structure (GS)	Row	Row total
LC	.831	.109	.012	.048	.496	4,724
GV	.183	.810	.001	.005	.459	4,373
AW	.476	.167	.345	.012	.009	84
GS	.029	.696	.000	.275	.036	345
Column	.501	.453	.009	.037	1.00	
Total	4,777	4,311	90	348		9,526

The *Class* database. Table 7 shows a one-step 4-state transition probability matrix which was derived from the data of transactions with the *Class* database. This database was used by a class of graduate students enrolled in an M.Sc. in information systems in 1994. Users essentially worked on the *Class* database in normal working hours of weekdays. Transactions over weekends or outside normal working hours were found to have little influence on long-term behavioral patterns of users; therefore, 526 transactions were excluded from further analysis under this category. Users in this group have similar rates of accessing the database. A transition probability from state i to state j in the matrix was estimated as the mean of the corresponding transition probabilities of individuals. Therefore, the resultant first-order Markov model describes the dynamics of how this database was used in normal working hours from Monday to Friday.

The maximum likelihood estimates of the transition probabilities were based on 8,386 valid transactions. It is useful to (see Kemeny & Snell 1960) classify the states of a Markov chain according to whether it is possible to go from a given state to another given state. In particular, the states are divided into equivalence classes. Two states are in the same equivalence class if they communicate, i.e., one can move from either one state to the other. The resulting partial ordering shows the possible directions in which the process can proceed (not necessarily in one step). For the *Class* database, the process can proceed from a given state to any one of the 4 states ($i \rightarrow j$, i, j $= 1, 2, 3, 4$). It can be verified that the 4 states are ergodic, or non-transient states because it is the minimum set such that the process will never leave it once entered (Fig. 3).

The stationary probability distribution (.501, .460, .033, .006) of the Markov chain is an important indicator

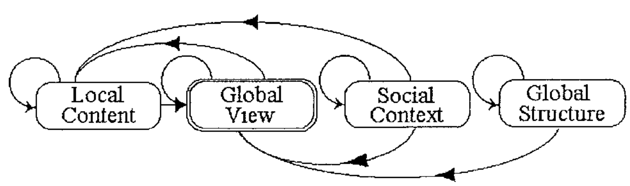

FIG. 2. The behavioral patterns of users with the *Groupware & Hypermedia* database.

of its limiting behavior. Users are much more likely to deal with the local content, or the global view of the database than to seek group awareness or to restructure the workspace. In particular, users are slightly more likely to work within the node content window than to the overview window in this database (.50 to .46). The probability of a persistent action on the focal node is .631, while a persistent action in the overview is .613.

The matrix also shows that an awareness seeking action tends to lead the process into actions on the local node

$$P[X_t = \text{LocalContent} \mid X_{t-1} = \text{Awareness}] = .468$$

whereas an action that changes the structure of the workspace is much likely to be followed by an action on the overview

$$P[X_t = \text{GlobalView} \mid X_{t-1} = \text{GlobalStructure}] = .813.$$

The matrix shows that the transitions are not symmetry between independent work modes (I: LC and GV) and loosely coupled modes (J: AW and GS) (i.e., $P_{IJ} < P_{JI}$), suggesting that there is a strong tendency of the process returning to the independent working mode.

Comparing with the matrix for the *Class* database, users of *Groupware & Hypermedia* are four times more likely to be constructing or modifying the structure of the database organization than seeking contextual awareness (odd ratio = 4.). In contrast, users of *Class* are 5.5 times more likely to seek contextual awareness than to work on the organization of the database.

The *Management* database. Figure 4 shows how the behavioral patterns differ between experienced and inexperienced users with the *Management* database. The global view played a central part in the behavioral patterns of experienced users, labeled as experts in the figure, in contrast to its role for novices. The global view absorbs users' actions from other categories of interactive behaviors. In addition, experienced users appeared to be more stable as they worked in a particular category. Inexperienced users were less likely to remain in a state longer than experienced users.

TABLE 7. First-order transition probability matrix for the database of the M.Sc.*class* in 1994.*

One-step transition	Local content (LC)	Global view (GV)	Group awareness (AW)	Global structure (GS)	Row	Row total
LC	.631	.315	.045	.009	.501	4,203
GV	.376	.613	.010	.002	.460	3,857
AW	.468	.241	.281	.011	.033	278
GS	.125	.813	.063	.000	.006	48
Column	.505	.452	.037	.006	1.00	
Total	4,239	3,793	307	47		8,386

Table 8 lists the weights which were used to derive the overall one-step transition model of using the MUCH system. The resultant model is slightly biased towards the most heavily used databases and user groups due to the weighting scheme. The weights are derived from transactions during normal working hours in weekdays and they are applied to the transactions in the same sample frame.

Let p_{ij} denote the transition probability from state i to state j over the observation unit t and $t + 1$ in the k-th dataset, w_k the weight assigned to the dataset, and p_{ij} the integrated transition probability from state i to state j over the 8 datasets. The following formula is used to compute the transition probabilities of the first-order Markov chain as being derived from 8 datasets:

$$p_{ij} = \sum w_k \cdot p_{ijk},\ i, j = 1, 2, 3, 4;\quad k = 1, 2, 3, 4, 5, 6, 7, 8$$

Table 9 shows the resultant transition probability matrix (p_{ij}). Since more weights are given to datasets from users who have been using the system more extensively in terms of the number of transactions, recurring patterns are highlighted by such weighting. Understanding recurring patterns in a normal process plays an essential role in achieving an overall understanding of the dynamics and complexity of using the system.

The n-th power of the first-order transition matrix predicts the probability of n-step transitions. As the interactive process evolves, the long-run probability distribution is independent from the initial probability distribution of all the possible states. Thus, the process is said to settle down to a stationary distribution. In this case, the expected stationary distribution is given by $P[s = LC] = .520$, $P[s = GV] = .437$, $P[s = AW] = .020$, and $P[s = GS] = .018$; $s \in S$ is the state to which the process moves in the next step.

The overall behavioral patterns of interacting with the MUCH system can be summarized in terms of the stationary distribution of the stochastic process. Users are predominantly engaged in transactions which are particularly related to the content of a chosen hypertext node ($p = .520$). To a less extent, users are engaged in transactions which manipulate an overview to the organization of hypertext databases, and provide entry points to the databases ($p = .437$). Users are much less likely to move into states such as seeking contextual awareness or constructing the databases ($p = .020$ and $p = .018$, respectively).

If the state LC and GV characterize an independent mode of working, and AW and GS characterize a loosely-coupled mode, users of the MUCH system are 25 times more likely to be engaged in the independent mode than in a loosely-coupled mode (odd ratio = 25.18). The interactive process moves from one mode to another in an unbalanced way; the process has a strong tendency to return to the independent mode once it enters into a loosely-coupled mode. Therefore, in general, users tend to use the databases in the MUCH as organization memory, rather than use them as a space for discussion, negotiation, or coordination.

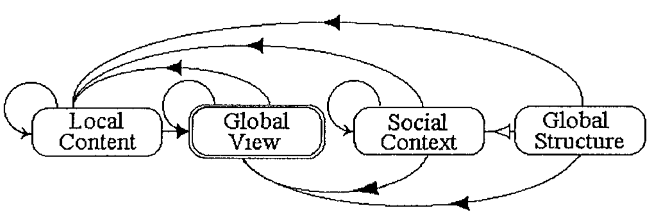

FIG. 3. The behavioral patterns of users with the *Class* database: Local Content and Global View fully communicate with each other.

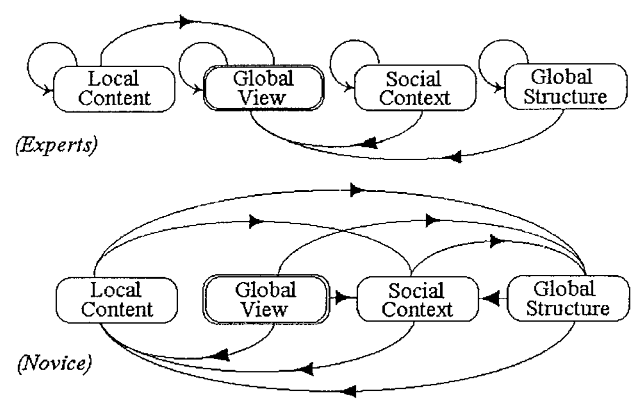

FIG. 4. The behavioral patterns of users with the *Management* database.

TABLE 8. Weights used to derive the one-step transition matrix over eight datasets.*

Preprocessed dataset	Transaction	Weight
Groupware & Hypermedia	9,526	.354
Class	8,386	.312
Management (R)	2,820	.105
Mangement (O)	2,479	.090
Oscar (R)	2,411	.089
General (R)	1,130	.042
General (O)	181	.006
Oscar (O)	103	.002
Total	26,855	1.00

* Recurring patterns are emphasized by being weighted in proportion to the overall number of transactions observed throughout these databases. R, regular users, O, occasional users.

Discussion

The analysis of the structure of collaborative writing with the MUCH system has resulted in some useful findings. These findings have implications for various aspects of the study of computer supported collaborative writing, such as improving the understanding of collaborative writing at various behavioral levels, providing an empirical basis for design formalization and evaluation, and generalizing the descriptive–prescriptive approach for studies in similar areas.

Markov Models

Markov models describe the dynamic transitions as well as the relationship between a sequence of actions and situations. This Markov chain analysis found that the underlying stochastic process on the experimental data is a second-order Markov chain. This finding was expected and it is also comparable to the findings in Qiu's study, that search patterns were modeled by a second-order Markov chain (Qiu, 1993).

Previous studies suggest search patterns in hypertext are a second-order Markov model, but Markov modeling techniques have not been used to study the dynamic structure of computer supported collaborative writing. In this study, the essential structure of collaborative writing with the MUCH system is adequately modeled by a second-order Markov chain. This finding quantifies the degree of complexity in the dynamic structure of collaborative writing with the MUCH system. This finding provides references for subsequent studies of collaborative writing with different systems in different contexts.

Behavioral Process

Qiu (1993) found that the search strategy with a hypertext system is similar to traditional information retrieval strategies. The transition of Browsing → Browsing → Browsing occurred 2.13% in her study, whereas in our study this pattern occurred in 17.68% of the second-order transitions. This difference may be caused by several reasons. For instance:

1. The number of nodes and links in the databases of the MUCH system is much larger, at least by a factor of 10, than that of the hypertext used in her laboratory study. A search path in the MUCH system is often longer and more complicated. Users may need to use Browsing repeatedly to locate some appropriate nodes in collaborative writing.
2. The structure and content of these databases in the MUCH system are subject to change by collaborators all the time. Browsing is an appropriate, heuristic strategy to deal with the dynamics.

TABLE 9. Integrated transition matrix over eight datasets (for use in the morning and afternoon, Monday to Friday).*

Power	Local content (LC)	Global view (GV)	Group awareness (AW)	Global structure (GS)
P(1)				
LC	.750	.197	.024	.027
GV	.271	.721	.004	.002
AW	.453	.274	.259	.013
GS	.056	.789	.021	.133
$P(1)^{10}$				
LC	.520	.437	.020	.018
GV	.517	.435	.020	.017
AW	.520	.437	.020	.018
GS	.518	.437	.020	.017
$P(1)^{12}$				
LC	.520	.437	.020	.018
GV	.520	.437	.020	.018
AW	.520	.437	.020	.018
GS	.520	.437	.020	.018

* The limiting behavior of the process appears to be converging as shown by the matrix at the 10th power of the original matrix.

3. The MUCH system provides a fisheye view browser to resolve the problem of accessing a large and evolving collaborative hypertext (Chen et al., 1994). In the category of Browsing, functions such as Unfolding and Folding are essential ways for users to move through the hypertext.

The contrast between the predominant pattern Browsing → Reading → Writing in our study and the Querying → DisplayTitle → DisplayArticle in Qiu's study suggests that the difference distinguishes a process of collaborative authoring from a process of information retrieval.

Empirical studies in laboratory settings found that experienced users of hypertext systems tend to use browsing strategies more than inexperienced or novice users (Carmel, Crawford, & Chen, 1992). Experienced users tend to explore wider areas in a hypertext network, whereas inexperienced users tend to use backtrack to minimize the effects of getting off the main search paths. Our study found regular users access wider areas in the shared workspace to adjust their views of a changing context for their actions. This finding has an implication for the design of hypertext database systems. A hypertext database system should provide sufficient facilities for experienced users to deal with the issues such as how to visualize a large hypertext database, and how to balance the local details and the global structure.

The results of the impact of users on the interactive process find that there is a difference in the awareness required between regular and occasional users. Regular users are more concerned with the social constructive nature of the shared workspaces.

Identified patterns reflect various needs for contextual-social awareness information. Each category of collaboration needs is characterized by a unique set of transitions between the strategic patterns and the depth of involvement. The results suggest that there is no single factor that can reliably predict these needs. These needs tend to be determined dynamically and interactively.

Implications of the Findings

The findings presented in this article have implications for various aspects of the study of computer supported collaborative writing, such as improving the understanding of collaborative writing at various behavioral levels, providing an empirical basis for design formalization and evaluation, and generalizing the descriptive-prescriptive approach for studies in similar areas. Stochastic models of user behavior with the MUCH system indicate that users spend about the same amount of time between dealing with the structure of a collaborative hypertext and concentrating on its content. This pattern suggests that navigation, or browsing, is the essential way to locate particular content material in collaborative hypertext. The question is whether this behavioral pattern is due to the lack of effective locating mechanisms in the MUCH system.

The MUCH system does provide some mechanisms to cope with the cognitive overhead for users facing a large and complex hypertext. For instance, the MUCH system can provide a filtered view of the organization of the shared hypertext according to the specified patterns by users. Users have complained about the filter because the filter seems to stripe off the context and display isolated nodes and distorted links. An alternative to the filter is the word frequency index posted over the node headings in the overview window. Chen, Rada, and Zeb (1994) show that the fisheye view browser extended with the word frequency index significantly improves the efficiency and effectiveness of locating target nodes.

The excessive use of browsing highlights another problem that must be addressed by a large and evolving collaborative hypertext; users need to know which part of the collaborative hypertext is new and what has been changed. Users of the MUCH system cannot easily tell which node is recently created and which link has been recently modified. There are two possible solutions. One is to provide notification mechanisms to inform the parties concerned what changes have been made. One is to visualize various changes that have taken place. Some existing systems, for example, the World Wide Web browser Netscape, have utilized these techniques.

The role of a behavioral model is to inform both users and designers of the system about the design, how it is used, and what the weaknesses are for a particular design feature. The models can highlight the source of the problem and how collaborative writing is affected by the use of a computer system. In this study, the focus of the implications is how users' navigating, outlining, and writing behaviors are affected by the use of the MUCH system, their experience with the system, and the work itself.

Limitations

To understand the dynamics of collaborative writing fully, one needs to take into account both social and technological aspects of the dynamics. For instance, how is the mutual understanding changed as participating individuals interact with the shared artifacts of collaborative writing? How do they utilize a broad range of facilities to organize and coordinate their work? Markov chain models to be constructed in this research are appropriate for capturing the dynamics of collaborative writing as users interact with the MUCH system as a tool.

The MUCH system is installed in an open environment of *X*-windows. Users have full access to other software applications in the environment. Users may choose to use electronic mail, telephone, or face-to-face meetings to communicate with each other. It is difficult, ethically as well as technically, in practice to keep track of the behavior of a group of people in a distributed environment by videoing them, recording phone conversations, and sharing individuals' E-mail messages. Observation methods such as videoing or watching may be non-obtrusive, but they may suffer from the *hawthorne* effect, that is, users may change their behavior simply due to the fact that they know they are being observed. A proper balance needs to be maintained regarding ethics, resources, and trade-off considerations.

Conclusion

Based on the statistical tests and Markov chain models, this study reached some conclusions about the dynamic structure of collaborative writing with the MUCH system in particular and about the significance and potentials of the modeling techniques used in this study.

Collaborative writing with the MUCH system is essentially characterized by behavioral patterns of an independent mode of interaction. The process of interaction only occasionally moves away from the independent mode to a loosely-coupled mode, which consists of behaviors concerning the influence of other users, such as awareness-seeking and communicating. The process has a strong tendency towards the independent mode. Interdependence among collaborators over a shared workspace is affected by various factors, such as the group, commitments of group members, and tasks.

Collaborative writing with the MUCH system is dominated by the use of writing support facilities for tasks such as exploring ideas, outlining, and local composition. The system has a much less active role in terms of the use of its facilities for collaboration. The issue of balancing writing support versus collaboration support has been addressed in some previous studies (see Neuwirth et al., 1994). However, previous studies are often based on subjective and anecdotal views from users, whereas this study is based on stochastic analysis of behavioral patterns at detailed levels. These behavioral patterns are empirically captured and examined via Markov chain models. Markov chain models are necessary for capturing the nature of collaborative writing at behavioral levels. The descriptive–prescriptive approach helps investigators to focus on the essence of human–computer interaction in collaborative writing.

In addition to high-level writing strategies such as planning, drafting, and revising, Markov chain models of collaborative writing highlight behavioral patterns for browsing, awareness-seeking, and balancing between local details and the global structure of a large collaborative hypertext. Transitions with predominant probabilities require special consideration and support from the underlying computing infrastructure for the work.

The descriptive–prescriptive approach in this study has shown appealing potentials of a powerful method and we conclude that it is worth pursuing. The significance of the Markov chain approach is in the heuristic power of a descriptive–prescriptive approach, which may lead to a fruitful integration with the mainstream practice of software engineering. For instance, the prescriptive nature of Markov chain models may provide a good basis for a formal specification of a CSCW system, whereas the descriptive nature of such models may lead to a more efficient empirical verification of formal models. Moreover, techniques for decomposing a large state space can be valuable for investigators to focus on problems with reduced complexity. A wide range of empirical data can be used for conducting Markov analysis across different systems and collaboration settings. Further work is needed to incorporate additional dimensions of collaborative writing into the descriptive–predictive model and more importantly, to integrate the state transition modeling techniques with the mainstream practice of software engineering so as to narrow the gap between dynamic and formal aspects of computer supported cooperative work.

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