On Individual Web Usage Trajectories: Implications for Electronic Commerce and Public Policy

Mario Christ
Graduate School of Distributed Information Systems Berlin Brandenburg
Humboldt University Berlin, Institute of Information Technology
Spandauer Str. 1, 10178 Berlin, Germany
Christ@wiwi.hu-berlin.de

Ramayya Krishnan, Daniel Nagin
Heinz School of Public Policy and Management
Carnegie Mellon University, 4800 Forbes Avenue, Pittsburgh, PA 15213, USA
RK2x@andrew.cmu.edu, DN03@andrew.cmu.edu

Oliver Guenther
Graduate School of Distributed Information Systems Berlin Brandenburg
Humboldt University Berlin, Institute of Information Technology
Spandauer Str. 1, 10178 Berlin, Germany
Guenther@wiwi.hu-berlin.de

Abstract

Over the last five years we have seen an exponential growth in the number of Web sites in the Internet. While the number of users making use of the Internet and the Web has also grown tremendously, at the level of the individual, little is known about the trajectory of change over time in the number of visits to Web sites. For example, we do not know whether the growth in Web usage is attributable to increased numbers of users or to increased intensity of use of established users or both. Moreover, little is known about how often users visit Web sites. This paper reports the results of an analysis of 156 weeks of longitudinal data on residential Web usage. This data was assembled as part of the CMU HomeNet project. Based on recent advances in semi-parametric, group-based statistical modeling, we examine whether there are distinctive clusters of Web usage trajectories. We find
that Web users can be clustered into four groups with distinct trajectories of use. These groups achieve saturation in their extent of Web usage as measured in the number of distinct Web sites they visit over time. We also report demographic profiles of the identified groups, discover significant demographic differences that distinguish these groups, and discuss qualitatively the trajectory of the number of page hits of individuals in these groups over time. These results have important implications for electronic commerce and public policy.

1. Introduction

With the commercialization in the Internet, the Web has become a marketplace. Visits at given Web sites are considered an important measure of market share and success, and indeed, many Web sites have enjoyed a steady increase in the number of visits. Yet at the level of the individual, little is known about the trajectory of change over time in number of visits to Web sites. Our study reveals that this increase is due to the immense growth in the number of Web users rather than an increase in Web usage at the individual level.

Figure 1 shows that over the period 1995 to 1998 there was an explosive growth in number of web sites available to users. In view this exponential growth, it is reasonable to expect that this increase in visiting opportunities has increased individual Web usage at least among some groups of people. To test this hypothesis we made use of a new statistical method [17] developed for psychologists to assist in the identification of groups of individuals with similar trajectories of development. Our objective is to use this method for the purpose of identifying distinct groups of “developmental trajectories” of Web usage. To do this the method
was applied to data from the HomeNet project at Carnegie Mellon University [13].
The HomeNet project has collected data on individual Internet usage and demographics from a panel of users from 1995 onwards, when the Net became popular.

A developmental trajectory describes the developmental course of a behavior over time. Here we apply this method for the first time to the 'development' of Web usage. We focus on the analysis of the number of distinctive Web sites accessed over time as a measure of the user’s interest in the World Wide Web. The method allows us not only to identify groups with different levels of usage, it also identifies distinctive trajectories of the development of Web usage over time. It identifies for example, whether some groups of people follow a trajectory of exponential growth in Web sites visited while others display a pattern of initial growth followed by steady decline. The resulting trajectories are compared to the overall trend in the number of Web sites, which multiplied exponentially in the period of observation.

The paper is organized as follows: Section two briefly describes our data, the HomeNet project at Carnegie Mellon University. Section three describes the semi-parametric, group-based statistical methodology and its application to the HomeNet data. Section four presents the identified trajectories of Web usage. Section five reports the group profiles and section six discusses qualitatively the analysis of page hits in the Web by individuals over time. Finally, section seven discusses the implications for electronic commerce and public policy.

2. The HomeNet Project at Carnegie Mellon

We use data from the HomeNet project, which is a field trial at Carnegie Mellon University whose aim is to understand people’s use of the Internet at home [13]. Starting in 1995, it provided families with hardware, Internet connections, and training. HomeNet carefully documented their usage of on-line services such as electronic mail, computerized bulletin boards, chat groups, and the World Wide Web. The number of individuals in the project grew from 156 in early 1995 to 339 in early 1998. Specifically, the HomeNet data is assembled from five sources:

- Computer-generated use records of electronic traffic, newsgroups read and posted to, Web sites visited, and time on the Internet
- Pretrial, bimonthly, and post trial questionnaires
- An archive of HomeNet newsgroup messages
- A log of help requests
- Home interviews

We use computer generated use records on Web sites visited and demographic data from questionnaires for our purposes. Our period of observation is 156 weeks from early 1995 to early 1998. Unlike prior studies ([22], [15], and [2]) that relied on highly non-representative samples (e.g., individuals who worked or studied in computer science departments) this study relies on a sample of households that is
more closely representative of the general population. Our period of observation, 156 weeks, is far longer than in prior studies. In our judgment an extended period of observation is required to calibrate credibly patterns of change in web use.

A major finding of the HomeNet project was that demographic factors – generation, race, and gender – rather than socioeconomic factors – income and education – or psychological factors – like social extraversion and attitudes towards computing – were the major factors that influence use. The fact that neither household income nor education predict Internet use, does strongly suggest that if economic barriers to Internet access were removed, people across socioeconomic lines would use the Internet. However, gender, race, and generation were all strong predictors of Internet use in the sample. For example, teenagers turned out to be much heavier users than their parents, and among teenagers, boys are heavier users than girls. Through detailed monitoring of family’s Internet use, periodic surveys, and interviews with family members, the HomeNet project measures the demand for and impact of electronic communication and telecommunication services over time. Further information about HomeNet is presented in [9].

3. A Semiparametric, Group-Based Approach for Analyzing Developmental Trajectories

A trajectory describes the pattern of change of a behavior over time. [17] describes a distinct semiparametric, group-based approach for modeling trajectories. This group-based modeling-approach assumes that the population is composed of a mixture of distinct groups defined by their trajectories. For example, do some groups of people follow a trajectory of exponential growth in Web sites visited while others display a pattern of initial growth followed by steady decline?

The multinomial modeling strategy described in [17] provides a flexible and easily applied approach for identifying distinctive clusters of individual trajectories within a given population and for profiling the characteristics of individuals within the clusters. Technically, mixtures of probability functions, suitably specified to describe the data to be analyzed are used in model estimation [14,16-20]. In order to allow substantial cross-group differences in the shape of trajectories, the parameters that characterize the trajectory of each group are left to vary freely across groups.

There are several advantages of the method. It allows direct testing of whether trajectories predicted by theory are actually present in the population. Furthermore, it provides an alternative to using assignment rules based on subjective categorization criteria to construct categories of developmental trajectories. This method also provides a formal basis for determining the number of groups that best fits the data and also provides an explicit metric, the posterior probability of group membership, for evaluating the precision of an individual’s assignment to a specific group. The pitfalls of constructing groups with subjective classification procedures, such as overfitting – creation of trajectory groups that only reflect random variation – are avoided. The data themselves are used to identify the number of groups that best fits the data and the shape of the trajectory for each group. Finally, the data
also provide an estimate of the proportion of the population whose measured behavior conforms most closely to each trajectory group.

The method can handle three different data types - count, binary, and psychometric scale data. We measure the intensity of web usage by number of distinctive web site accessed per months. Therefore, for the purpose of this article, which analyzes a count of distinctive Web sites visited, we focus on count data only.

To clarify the concept of distinctive sites, table 1 reports the web usage patterns of a hypothetical user over a three-month period. In period 1 the user accesses three sites but only two are distinctive, Yahoo is visited twice and Amazon once. By this same counting logic, four sites are visit in period 2 but only three are distinct. In month three two sites are visited but it is the same one so only one distinctive site is visited.

<table>
<thead>
<tr>
<th>Month</th>
<th>URLs accessed</th>
<th>#distinctive Web sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td><a href="http://www.yahoo.com">www.yahoo.com</a> <a href="http://www.yahoo.com">www.yahoo.com</a></td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 1: URL sets and number of distinctive Web sites of a fictitious user**

The count data \{2,3,1,…\} is assumed to be generated by an underlying Poisson process. Specifically, for each group j, it’s rate of Internet usage in week t following installation of the Internet connection, \( \lambda_{jt} \), is assumed to follow a third order polynomial:

\[
\log(\lambda_{jt}) = \beta_0 + \beta_1 \text{week}_t + \beta_2 \text{week}_t^2 + \beta_3 \text{week}_t^3
\]  

The shape of the trajectory can vary by suitably setting \( \beta_0, \beta_1, \beta_2, \) and \( \beta_3 \), the model’s coefficients. They are superscripted by \( j \) to denote that the coefficients are not constrained to be the same across the \( j \) groups. This flexibility allows for easy identification of population heterogeneity not only in the level of behavior at a given week but also in its development over time. The parameters of interest - \( \beta_0, \beta_1, \beta_2, \) and \( \beta_3 \) - are the product of maximum-likelihood estimation. For a detailed derivation of this likelihood see [17].

---

1 A log-linear relationship between \( \lambda_{jt} \) and \( \text{week}_t \) is assumed to ensure that the requirement that \( \lambda_{jt} > 0 \) is fulfilled in model estimation.
The selection of the model that fits the data best involves: (a) determination of the optimal number of groups to compose the mixture and (b) determination of the appropriate order of the polynomial used to model each group’s trajectory, where order refers to the degree of the polynomial used to model the group’s trajectory. For example, a second-order trajectory is defined by a quadratic equation, a first-order trajectory is defined by a linear equation in which $\beta_j^2$ and $\beta_j^3$ are set equal to zero, and a zero-order trajectory is defined by a flat line in which $\beta_j^1$, $\beta_j^2$ and $\beta_j^3$ are set equal to zero. We follow the lead of [5] and use the Bayesian information criterion (BIC) as a basis for selecting the optimal model. For a given model, BIC is calculated as follows:

$$BIC = \log(L) - 0.5 \times \log(n) \times (k)$$

where $L$ is the value of the model’s maximum likelihood, $n$ is the sample size, and $k$ is the number of parameters in the model. [12] recommends selection of the model with the maximum BIC. Since BIC is always negative, the maximum BIC will be the least negative value.

Once the model that fits the data best is found, for each individual $i$ the probability of membership in group $j$ can be calculated on the basis of the individual’s longitudinal pattern of behavior. Furthermore, demographic factors that distinguish the populations of the various trajectory groups can be identified easily.

The software used to estimate these models is a customized SAS procedure that was developed with the SAS product SAS/TOOLKIT. It is available at [21] and is described in detail in [11]. Alternative methods of model estimation are discussed in [17].

4. Developmental Trajectories of Web Usage in the HomeNet Data

Figure 2 depicts the average utilization for the entire sample over the study period. Observe that in contrast to the exponential growth in Web sites available as shown in figure 1, there is in actually a large decline in the average number of distinctive Web sites accessed. However, this population average may be concealing important heterogeneity across subgroups. In particular, it is possible that there are some groups of heavy users, non-users, moderate users etc., which balance each other out. Different groups of people may exhibit different kind of behavior.

We applied the method described in the previous section to the HomeNet data on individual Web usage to test for the presence of such heterogeneity. We consider the trajectories ‘learning curves’ of Web usage. Our purpose is to test whether the obvious changes in the Web between 1995 and 1998, such as rapid increase of the number of Web sites available, commercialization of the Net and the advent of banner ads, have a positive impact on these ‘learning curves’. All of the sampled households initiated their Web usage in this period of dramatic change in the Internet.
Based on the Bayesian information criterion we find that Web users can be clustered into four groups with distinct trajectories of use. The four-group model has the polynomial orders of 2, 2, 2, and 3 for the groups 1, 2, 3, and 4 respectively. Figure 3 depicts the results of the analysis of the HomeNet data. It displays the actual and predicted trajectories of the four groups which we label “very heavy users”, “heavy users”, “moderate users”, and “non-users”. Also, because the utilization rates of the latter two groups are so much lower than the former two groups, figure 4 is included showing only learning curves of the moderate- and non-user groups. The solid lines represent actual behavior and the dashed lines represent predicted behavior.\(^2\) Table 2 reports the estimated proportion of the population belonging to each of these groups.

\begin{table}[h]
\centering
\begin{tabular}{|l|c|}
\hline
Group & Percents \\
\hline
Non-users & 49.9% (174) \\
moderate users & 35.5% (120) \\
heavy users & 10.2% (33) \\
very heavy users & 4.3% (12) \\
\hline
\end{tabular}
\caption{Group percentages}
\end{table}

\(^2\) Predicted behavior is calculated as the expected value of the random variable depicting each group’s behavior. Expected values are computed based on model coefficient estimates. In regard to count data, this expectation equals the antilog of Equation 1. Actual behavior is computed as the mean behavior of all persons assigned to the various groups identified in estimation. As described below, the assignments are based on the posterior probability of group membership.
The group of ‘non-users’ was composed of individuals who, but for a few visits to Web sites immediately after the start, basically did not use the Web throughout the observation period. This group accounts for estimated 49.9% of the sampled population. The saturation level of ‘non-users’ is close to zero, indicating that this group did not find the Web useful, following a short period of ‘surfing around’ or ‘exploring’ the Web. The second group of individuals – moderate users - start Web usage at a higher level and follow a downward path in Web usage to a point of saturation between 3 and 4 distinctive Web sites per week. This group is estimated to constitute 35.5% of the population. Among the population that actually uses the Web (group 1 excluded) it accounts for 70.9% of the population.

The third group - heavy users - initiate Web usage at a high level between 25 and 30 distinctive Web sites per week. However, thereafter for the period of observation their utilization steadily declines. Their saturation point cannot be estimated, however, it seems to be somewhere below 10 distinctive Web sites per week. This group accounts for 10.2% of the overall population or 20.4% of the Web users.

Figure 3: Number of distinctive Web sites accessed at a given week
Finally, a ‘very heavy user’ group was identified and is estimated to make up 4.3% of the overall population or 8.6% of the Web using population in the HomeNet sample. This group consists of users who started at a very high level, nearly 70 sites per week and who, aside from some modest temporary increases and decreases, settle into a usage rate of about 50 sites per week.

In summary, all the groups achieve saturation in their extent of Web usage as measured by the average number of distinctive Web sites visited per week. This saturation level is independent of the number of Web sites available. For 49.9% of the population called ‘non-users’, this saturation level is close to zero. For ‘moderate users’ who account for 70.9% of the people who actually use the Web, this saturation level is about 4 distinctive Web sites per week. ‘Heavy users’ tend to visit nearly 10 distinctive Web sites per week. A minority of very heavy users has a saturation level that is about 50 distinctive Web sites per week.

The method allows direct testing of whether trajectories predicted by theory are actually present in the population. The hypothesis of finding at least some groups that follow the overall trend of increasing number of distinctive site visits cannot be confirmed. On the contrary, all the groups follow a downward path, indicating that, after a period of ‘surfing around’ and ‘exploring’ the Web users seem to focus on a limited number of sites. This is particularly the case for the large group of ‘moderate users’. Apart from the group of ‘heavy users’, given clusters of users do not change behavior much over time. The increase of available Web sites did not lead to an increase of Web usage on the individual level. There is no evidence for an upward trend. This is of particular interest if one considers the dramatically
increasing number of banner ads in the Web, which are supposed to trigger a higher number of visits to distinctive Web sites. This does not seem to be the case for the three year long trajectory groups identified in the analysis. Note that there might be individuals who actually show an increasing Web usage pattern. However, our analysis reveals that this group, if it exists, is not large enough to form a distinctive group of individuals.

5. Group Profiles

As a next step we analyzed which demographic factors characterize the identified clusters and developed profiles of these different user groups. One major finding of former analysis of the HomeNet data was that social demographics rather than socioeconomic and psychological factors were the major determinants of use [13]. Therefore we focused on variables such as gender, race and position in the family rather than income and education. Table 3 shows the demographic differences across the various groups.

<table>
<thead>
<tr>
<th>Percentage</th>
<th>all users</th>
<th>non-users</th>
<th>moderate users</th>
<th>heavy users</th>
<th>very heavy users</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adult</td>
<td>59.3%</td>
<td>63.2%</td>
<td>57.5%</td>
<td>51.5%</td>
<td>41.7%</td>
</tr>
<tr>
<td>Female</td>
<td>55.1%</td>
<td>61.6%</td>
<td>54.2%</td>
<td>39.4%</td>
<td>33.3%</td>
</tr>
<tr>
<td>Minority</td>
<td>29.8%</td>
<td>39.7%</td>
<td>19.8%</td>
<td>15.2%</td>
<td>16.7%</td>
</tr>
</tbody>
</table>

Position:

<table>
<thead>
<tr>
<th></th>
<th>Mom</th>
<th>Dad</th>
<th>Daughter</th>
<th>Son</th>
<th>Other</th>
<th>Avg. age</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adult</td>
<td>26.8%</td>
<td>19.5%</td>
<td>23.6%</td>
<td>18.9%</td>
<td>11.2%</td>
<td>30.7</td>
</tr>
<tr>
<td>Female</td>
<td>31.6%</td>
<td>16.1%</td>
<td>23.0%</td>
<td>16.7%</td>
<td>12.6%</td>
<td>31.6</td>
</tr>
<tr>
<td>Minority</td>
<td>25.0%</td>
<td>25.0%</td>
<td>28.8%</td>
<td>17.5%</td>
<td>6.7%</td>
<td>30.6</td>
</tr>
<tr>
<td>Position</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>28.3</td>
</tr>
</tbody>
</table>

Table 3: Overview of characteristics of users in the various groups

The summary statistics reveal that individuals in the groups that use the Web heaviest tend to be younger, male, and white. Teenagers, particularly boys, use the Internet substantially more than their parents. These results agree with [13].
6. **Intensity of Web Utilization per Site**

As discussed, we did not find any evidence of increasing individual web usage using the distinct number of Web sites visited as a measure of utilization intensity. As a next step, one could think of testing the robustness of this finding using an alternative measurement of intensity of Web use, namely the number of page hits per month. [3] finds that the finding of saturation in Web usage in the HomeNet sample is not dependent on the specific measure of number of distinct Web sites visited per month. An analysis of the distribution of page hits over time leads to the same conclusion. The number of page hits in the HomeNet sample decreases over time.

In general, the number of page hits per site indicates how satisfied users are with a given site. If users in fact view many pages on a given site, it is likely that this site interests them. Therefore, we see the need for measuring the intensity of utilization, e.g., as measured by numbers of page hits per site. A high number of page hits per site would indicate that individuals are making multiple visits to Web sites, which is desirable from the perspective of a Web site operator (especially, if banner advertising was a significant source of revenue). Given the results discussed thus far that indicate saturation in numbers of distinct sites visited, the development (i.e., trajectory) of the number of page hits per site over time would give us additional insights in how one should think of Internet usage. If there were in fact an increasing number of page hits per site over time, users would visit sites over time more intensely.

Therefore, [3] investigate whether the intensity of usage as measured in page hits per site varies by trajectory group. Perhaps very heavy users do not revisit sites repeatedly. This may explain why they visit so many distinct Web sites. Conversely, non-users may be visiting a few Web sites with great intensity. However, [3] finds that all the groups have basically the same utilization intensity as measured by number of page hits per site. They also reveal that the average numbers of page hits per site seem to converge across groups when users reach a steady state. There seems to be a fixed level of this ratio of about 5-6 hits per sites. Judging from these results, there is no such thing as user groups that have a particular high utilization intensity measured in page hits per site. The hypothesis that users with fewer distinct Web site visits have a higher number of page hits per site has to be rejected. The intensity with which people utilize their favorite Web site is surprisingly similar across user groups.

[3] also examined if the intensity rates of 5-6 page hits per site was an exaggerated summary statistic of the typical level of usage intensity, because users have a favorite portal they visit very often. Surprisingly, this does not seem to be the case. The numbers of page hits per sites does not change significantly when [3] controlled for the portal sites.
7. Conclusion: Implications for Electronic Commerce and Public Policy

In this analysis we have examined the per weekly trajectories of visits to distinctive Web sites over a 156 week period. It is important to keep in mind that individuals do not necessarily visit the same distinct Web sites from week to week. Indeed, there might be considerable churn in the specific Web sites visited from week to week. In this case, there would be limited overlap over time in the identities in the specific Web sites visited. However, the basic idea of saturation of Web usage still holds under the assumption of constant churn over time.

The relevant implication for electronic commerce on the Web are the following: The study reveals that, due to a saturation point in Web access behavior, the number of visits at a given Web site is unlikely to be increased on the individual level. On average, the growth of visits at Web sites is rather a result of an increasing number of Web users than a result of increased usage on the individual level. This leads to the conclusion that there exists, for each given individual, a fixed level of preferred Web usage, which is independent of the number of Web sites offered. On the individual level, the competition for Web users seems to be a zero sum game. On average, winning a user for one Web site means loosing this user to another site. Means of Web commercialization such as the advent of banner advertisements, which became common in the Web during the period of our study, does not seem to lead to an increase in Web usage in terms of visits to distinctive Web sites. The effectiveness of banner ads, which are supposed to trigger a higher number of visits to distinctive Web sites, might be questioned. This confirms existing sources of consumer response data on banner ads that propagate that with increasing exposure to passive banner ads, the probability that a consumer will click on it becomes close to zero [6].

Apart from identifying groups of developmental trajectories, which lead to different points of saturation, we discovered distinctive demographic factors that distinguish these groups. Apart from the fact that the identification of demographic factors that characterize the clusters of developmental trajectories provides valuable insights from a marketing perspective, our results also have importance from a public policy perspective. Our findings confirm results of previous work on the HomeNet project, we find that race, gender, age, and role in the family are major correlates of Web use in general and saturation level in particular. These results speak to the digital divide debate. Studies such as [8] carefully examined the policy implications of demographic patterns of Web usage. When it comes to predictions how gender gap or race gap evolve over time, numerous studies [4] suggest that the gender gap closes over time whereas the race gap prevails [1]. [7] suggests that ensuring access to the Web almost automatically triggers usage and thereby helps closing the digital divide.

We wished to examine if access to the Web automatically translates into usage by analyzing if there exists a race or gender gap in our sample, which consists of people who have access to the Web. Judging from the results reported in table 3, the key users in our study are white males, whereas the non-users are minorities and
women. For example, the percentage of people who belong to a minority group is 29.8% in the overall sample, 39.7% for non-users, 19.8% for moderate users, 15.2% for heavy users, and 16.7% for very heavy users. This seems to support the need for public policies designed to encourage all segments of people to use the Internet. Even though all the users in our sample had access to the Internet for free, yet we saw these differences. The problem is not simply one of having access, but rather of having the capacity plus the interest in using this technology. Following this sequence, there seem to be more sites in the Web that speak more to white males.

Groups of people follow trajectories for visits to particular commercial Web sites as well. Further research is necessary to analyze the usage pattern of individuals for these sites. Counts of buy orders at a given commercial Web site are undoubtedly data that should be analyzed in further research. Furthermore, demographic factors that discriminate clusters of trajectories on particular commercial Web sites are likely to change from one Web site to the next.

In general, the rejection of the hypothesis of increasing Web usage in terms of distinctive Web sites visited becomes important when the growth in terms of numbers of people accessing the Web slows down. Then, competition among Web companies for Web market share is likely to become fiercer.

Further, the issue of churn has to be analyzed in more detail. If indeed there is considerable churn, users maybe effectively visiting different Web sites at random. Alternatively, and we believe more plausibly, they maybe visiting Websites that are functionally related, e.g. vacation sites. If in fact this is the case, we need to develop methods for modeling churn, which take into account the possibility that Web sites maybe in some sense be complements and substitutes to each other.

Finally, the patterns of Web usage we found for usage data from 1995-1998 may be different for more recent data. Note that the HomeNet project focuses on individuals at home. A significant part of the population accesses the Internet at work. Therefore, further research is necessary in order to confirm those patterns for all groups of users in the Web and for data from 1998 on. [13] describe the degree of representativeness of the HomeNet sample. We encourage further research with respect to more recent data over a longer period of observation with a truly random national or even international sample.

**Acknowledgements**

HomeNet is funded by grants from Apple Computer, AT&T, Bell Atlantic, Bellcore, Intel, Carnegie Mellon University’s Information Networking Institute, Interval, the Markle Foundation, the NPD Group, the U.S. Postal Service, and US West. Farallon Computing and Netscape Communications contributed software.

Development of the trajectory estimation method and software was supported by the National Science Foundation under Grant No. SBR-9513040 to the National Consortium on Violence and also by separate National Science Foundation grants SBR-9511412 and SES-9911370.
The author Mario Christ was supported by the German Research Society, Berlin-Brandenburg, Graduate School in Distributed Information Systems (DFG grant no. GRK~316). This research was also supported by the Humboldt Foundation, Berlin, Germany.

The work of Ramayya Krishnan was funded in part by NSF grant CISE/IIS/KDI 9873005.

**References**


