Exploring Different Affects of Internet Usages on Female Users' Social and Academic Behaviors

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***ABSTRACT**: Female students in real life have varying interests and hobbies and sometimes they are much different than males in terms of hobbies and behaviors. One of the main differences is their branch of study and undertaken course. Mostly male students are interested in engineering courses or branches, whereas females are interested in nursing, medicine or arts courses.*

Female students are in minority in most of technical institutions in India and many infrastructural facilities and services are not targeted to them. For example, computer centers and some of laboratories are open till 12 midnight. Female students may not be able to use them because of their hostel rules; they are expected to be back in their rooms before 8PM due to security issues. To minimize difficulties arising out of such situations, institutions provide some computing and Internet facilities in their hostels, and in general these facilities are limited. Even though Internet facilitates minimizing geographical, social and cultural barriers, there are no brief studies on any significant impacts of these facilities on professional, social and personal pursuits of female students.

Since, Internet provides an online life environment for users; we attempt to explore special behaviors of female students on Internet and the affects of these behaviors on their personal and professional life. This investigation is a deep study of female students' and faculty members'/professors' Internet usage behaviors in different periods of a semester. We attempt to analyze different affects of these behaviors on their personal, social and professional behaviors with the help of analyzing proxy server's access log files, which were collected for the period of 30 months, of an engineering college in India.

Keywords: Behavioral mining, Log file analysis, Internet usage behaviors, Proxy server logs, Web usage mining

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1. Introduction

World Wide Web (WWW) contains huge amounts of data (Web documents/pages) with different contents and structure. Users connect to the Internet based on varying needs/requirements/interests and visit various Web pages. Female students are in minority in most of the technical environments in India and most of the Asian countries. Therefore, no special infrastructural facilities or services are provided to them due to social and cultural barriers. In [1], *Jonathan Dutch* analyzed American female users' Internet usages and mentioned that, Internet facilitates removal of geographical, social and cultural barriers; it does not seem to have any significant impact on academic pursuit of female students. Since there are not many serious investigations have been conducted to study the usage patterns of Internet by female students and its impacts on their academic and social activities, we attempted to explore different aspects of Internet usages of female students and faculty members/professors during different days and periods and events in an engineering college. Our analysis would be helpful to proposing some techniques for providing better support and service to different groups of female's in universities based on their variety of Internet usage behaviors.

Websites are categorized under different categories [2, 3]. Our analysis is based on Website classification scheme, presented in [4], which is a content and structure based categorization scheme. In this classification scheme, authors categorized Websites into two main categories. These are Academic (AC) and Non-Academic (NAC) categories.

- AC Websites: includes all sub-categories which are related to academics such as journals and E-books or e-learning Websites, etc.

- NAC Websites: includes all sub-categories which are not directly related to academics such as Social networks, Personal Websites, Portals, etc.

Currently one of the main challenges in social networks analysis is analyzing affects of different categories of Websites usages on students' academic performance (CPI) or personal and social behaviors. Most of the parents and academic advisors have negative opinions about students' daily Internet usage especially NAC Websites usages and feels that this has negative effect on their academic performances (CPI). In this paper, we attempt to clarify different aspects of Internet usages regarding different categories of Websites visited and duration of time spent on Internet in different periods of a semester, and finally the affects of these behaviors on their academic performances.

This paper is organized in seven sections. Section II contains basic concepts and definitions related to this research. Section III presents related work. In section IV, we present data collection and pre-processing stage. Section V presents analysis of different aspects of Internet usage behaviors of female users. In section VI, we described the relationship between female faculty members'/professors' Internet and professional behaviors. Section VII concludes the paper.

2. Basic Concepts

This paper is one investigation of Web usage mining in educational environments'. In this section, we present some basic concepts and definitions related to data mining, web mining, behavioral mining, and social networks.

2.1 Data mining

Data mining is the process of extracting knowledge and interesting patterns from data. This process is depicted in Figure 1.

It is the analysis of (often large) observational data sets to discover unsuspected relationships and help to summarize the data in novel ways that are both understandable and useful to data owners [5, 6].

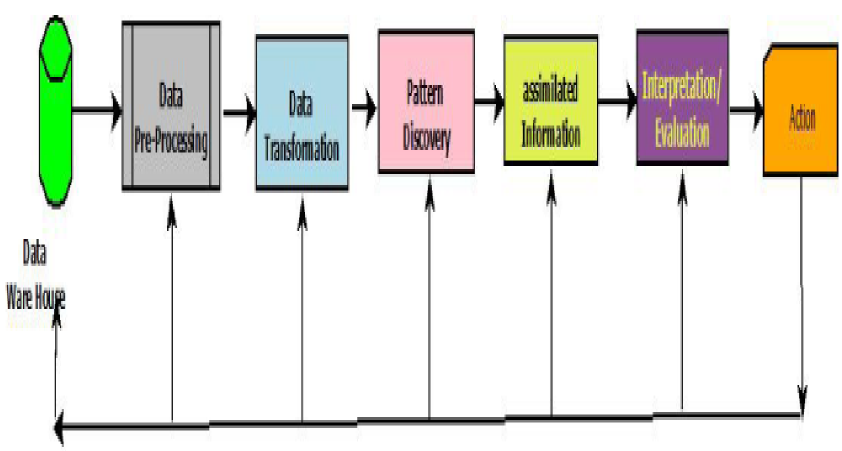

Figure 1. Process of Data mining

2.2 Web mining
Web mining is further appreciated as it utilizes the data mining techniques to automatically discover and extract information from Web documents and services. Tanimoto [7] had outlined various suggestions of using this technology for educational purposes. In [8, 9], authors classified some other applications of web mining.

Web mining is further includes the following three sub-categories [10, 12]:

1.1.1 ***Web Content Mining***: is concerned with the extraction of useful knowledge from the content of Web pages with the help of data mining techniques.

1.1.2 ***Web Structure Mining***: is a new area and is concerned with the application of data mining to the structure of the Web graph.

1.1.3 ***Web Usage Mining***: aims to discover users' interesting usage patterns by analyzing Web usage data that is stored in proxy server access log or server logs, etc. Web usage mining is mostly related to personalization. The process of Web usage mining [15] is presented in Figure 2 and further includes the following steps:

1.1.3.1 *Data Preprocessing*: Preprocessing consists of converting the usage, content, and structure information contained in various available data sources into the data abstractions necessary for pattern discovery.

1.1.3.2 *Pattern Discovery*: Pattern discovery draws upon methods and algorithms developed from several fields such as statistics, data mining, machine learning and pattern recognition [15, 16].

1.1.3.2.1 . *Clustering:* Clustering is a data mining (machine learning) technique used to place data elements into related groups without advanced knowledge of the group definitions. Popular clustering techniques include k-means clustering and expectation maximization (EM) clustering.
1.1.3.2.2 **.** *Classification:* Classification is the task of mapping a data item into one of several predefined classes [16].

1.1.3.2.3 **.** *Sequential Patterns:* The technique of sequential pattern discovery attempts to find inter-session patterns such that the presence of a set of items is followed by another item in a time-ordered set of sessions of episodes.

1.1.3.2.4 **.** *Dependency Modeling:* Dependency modeling is another useful pattern discovery task in Web mining. The goal here is to develop a model capable of representing significant dependencies among the various variables in the Web domain.

1.1.3.2.5 . *Association Rules:* Association rule generation can be used to relate pages that are most often referenced together in a single server session.

1.1.3.3 *Pattern Analysis:* Pattern analysis is the last step in the overall Web usage mining process. The motivation behind pattern analysis is to filter out uninteresting rules or patterns from the set found in the pattern discovery phase.

2.3 Behavior mining
Understanding users' behaviors on Internet can be helpful for business owners and administrators at educational environments. In business Websites might be used for making better plans for increasing productivity, quality and marketing in future, and in educational environments would be useful for administrators to make useful links based on users' favorite visited Websites.

Exploring Different Affects of Internet Usages on Female Students Academic and Personal Behaviors 5 Different applications of behavior mining exists including the fraud detection [17] and predicting users' future behaviors [18 ~ 23].

2.4 Social Networks
Several definitions for Social Networks exist in literature.

• A social network [24] is a social structure made up of individuals or organizations called nodes, which are tied (connected) by one or more specific types of interdependency such as friendship, common interest, financial exchange, dislike, sexual relationships, or relationships of beliefs, knowledge or prestige.

• Social networking [25] is grouping of individuals into specific groups like small rural communities or a neighborhood subdivision.

• A social network is defined as a social structure of individuals, who are directly or indirectly related to each other based on a common relation of interest such as friendship, trust, etc [26].

3. Related Work

Several research efforts [27 ~ 29] have been directed to understand users' behaviors by analyzing their Web access in the context of recommender system search. The empirical study conducted by Kathrin Figl [27] focused on discovery of relationships between university curriculum and opportunity to build a social network among students. In [28], authors focus was to understand relationships between students' academic performance and Web access behaviors. This understanding may enable us to design better Curriculum and infrastructure. If needed can improve quality of academic output.

Jo Sanders [30] presents survey of relationship between technology in education and gender. This is a detailed survey highlighting the gender related issues in education. Kim and Chang [31] study has concluded that computer usage have differential effects on academic performance of users from the immigrant and gender groups. It advocates adaptive design of multimedia contents for different groups of students addressing their specific needs. In [32], the role of social networks in students learning experiences has been studied. This study had been directed to analyze the role of social networks in students learning experiences and concluded that social networking places a positive role in students learning experiences.

Several researches efforts [33 ~ 35] have been directed to understand users' behaviors from different aspects. Many researchers explored educational environments different sources of data for analyzing students' behaviors and predicting final examination results, especially their attention were on recognizing at risk students before exam and notify to their teachers. Eytan Adar and D.S.Weld [33] focused on aggregation and comparison of users' behaviors and predict future usage patterns with the help of past history. Alaa El-Halees [34] developedn methods for extracting knowledge for describing students' behaviors, K.R.Suneetha, K.R.Krishnamoorthy [35] used Web mining techniques for mining log files for NASA Website, for finding users' visiting pages and common errors that users faced. Some researches focused on social networks analysis from different aspects [36 ~ 39], or social networks usage affects in educational area and students' performance [37]. Most of researches in educational data mining 6 Exploring Different Affects of Internet Usages on Female Students Academic and Personal Behaviors attempted to make prediction methods for future academic performance of students using different data [39 ~ 42].

Our study is focused on analyzing different aspects of Internet usage behaviors of female users and the effects of different behaviors on their personal and professional activities.

4. Data Collection and Pre-Processing

Our analysis for this paper is based on collected access log files from proxy server of Motilal Nehru National Institute of Technology, Allahabad, India, which are collected for a period of 30 months including five academic semesters. This period includes five final examination weeks' data in addition to mid-terms and test examination weeks. We are given permission to use access files for preprocessing and filtering contents for our research purpose. During preprocessing step, for preserving users' privacy, the actual identity of students' is hidden and replaced with a unique virtual id generated automatically.

Computer center provided all users' information including *user_id*, *full name*, and *department name* in the format of text files. Other data including students' academic information were collected at Dean (Academic Affairs) office for five semesters of three academic years, separately, in excel files. Fields included in a record are:

registration no, full name, program, branch, semester, gender, CPI, and Email

Because each day's log file had capacity of more than 500MB in size, the first attempt is concerned on reducing the size of access log files by removing unnecessary fields. Original file contains 11 fields per each record in its original file. For our analysis the following three fields are selected.

user_id, visited_Website's_URL, Time of Connection

Now, for our analysis, we have selected the following fields.

virtual_Id, program, semester, department, average_time_spent (per a day), average page hits (per a day), number of visited Websites (per a day), CPI (of before semester if exist).

An algorithm is developed to compute the time spent by users on different categories of Websites and the total time spent per a day by each user. Minute is used as a unit of time duration to measure the time spent by a user on a Website during a day. This unit of measurement implies that all durations less than a minute has been rounded to one minute. This algorithm computes the average time spent by each user per a day and also average time spent by him/her on different category of visited Websites. All pre-processed data are transferred in excel files and various records with inconsistent values including missing value are removed.

5. Analyzing Female Students' Behaviors from Various Aspects

Female students are in minority in India and most of the Asian countries. Current population of female students in Motilal Nehru National Institute of Technology, one of National Institution of Technology in India, is approximately 14% of all enrolled students. All students are provided a user ID for Internet and E- mail access.

Gender based students' populations in different programs which are based on data collected from Dean (Academic Affairs) office are presented in Figure 3.

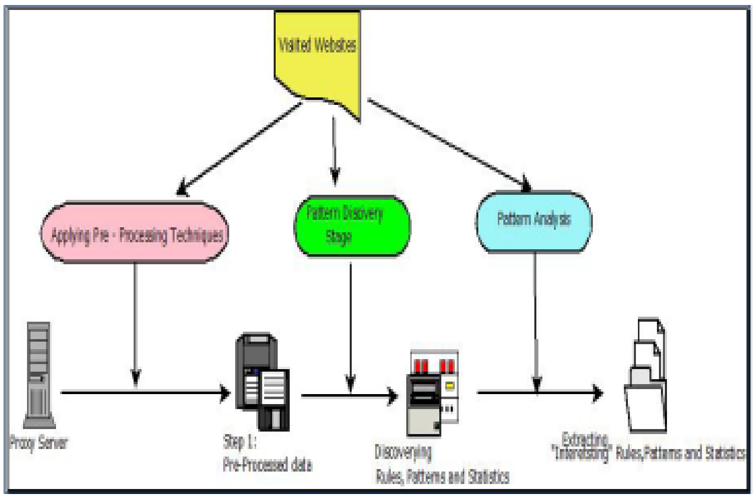

Figure 2. Web Usage Mining Process

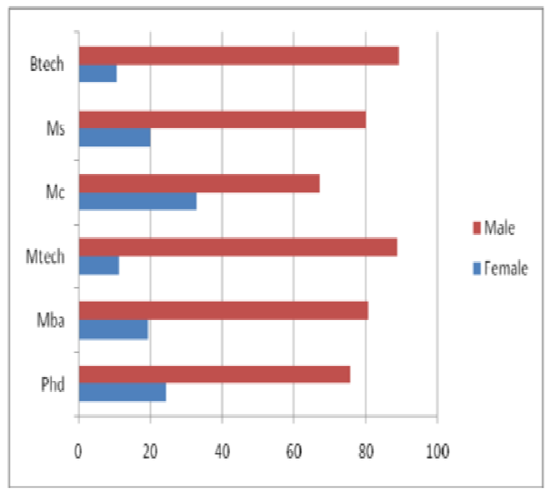

Figure 3. Gender Based Students' Population in Different Programs

In Figure 3, the horizontal axis shows the percentage of students' populations and the vertical axis shows different programs. This figure revealed that, there are brief differences within female and male students' populations almost in all of the programs. Majority of female students' are undertaken MCA program and minority of female students belongs to MTech and BTech programs.

In the first point of our analysis, we extracted the population of continual users, i.e., minimum of one time they had connected to Internet every day, even for a few minutes, during 30 months of our analysis data. Figure 4 presents continual female users' percentages in different undertaken programs.

In Figure 4, the horizontal axis represents different programs and vertical axis represents percentage of continual female users. From this figure, majority of female continual users belongs to Btech program's students and minority belongs to MBA. Different analysis have been shown that the MBA students are continual Internet users. We made different discussions with MBA students about the reasons for their less usage of Internet resources. Results based on these reports were shown that this is because of their subjects of study or lack of sufficient computer or Internet usage knowledge.

Our next observation is related to academic performance (CPI) of users. Figure 5 shows that on average female users are having 7.75 CPI in the scale of 0 to 10. This implies most of them are academically good students.

In most of colleges in India, students based on their CPI are categorized under 5 classes:

- 8.5 d” CPI d” 10 named as academically *excellent* students

- 7 d” CPI < 8.5 named as academically *very good* students

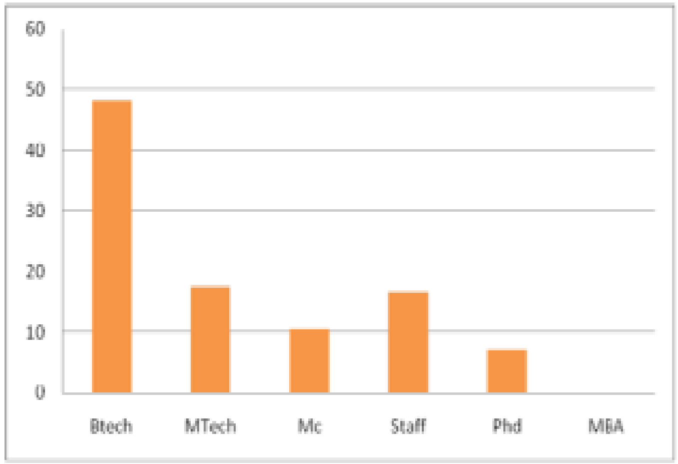

Figure 4. % of Continual Female Users with their Undertaken Program

- 6 d” CPI < 7 named as academically *good* students

- 5 d” CPI < 6 named as academically *medium* students

- 0 d” CPI< 5 named as academically *weak (at risk or failed)* students

Relationship between CPI and average time spent on Internet per a day in Internet by female users is shown in Figure 6. Based on this figure, most time spent belongs to students which had (5<=CPI<6) or academically medium students, but maximum number of visited pages (hits#) belongs to students with (6<=CPI<8) or academically good students.

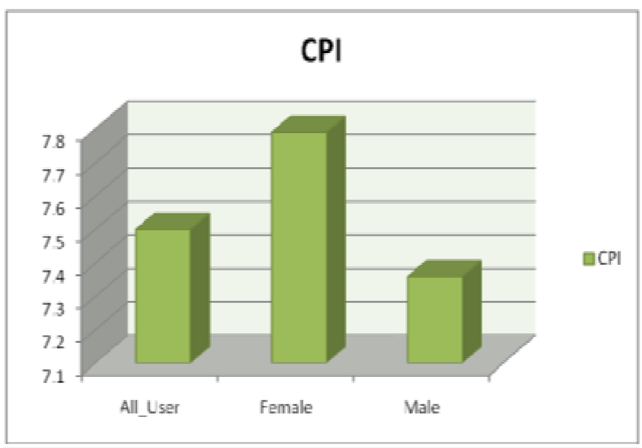

Figure 5. CPI of Female vs. Male

It is interesting to observe that minimum time spent on Internet per a day and minimum number of visited pages (hits#) belongs to students with (CPI<5) or academically weak students. This means that the weak students had less activity and usage from Internet in comparison to other students. Therefore this will be so interesting to look at this group of Exploring Different Affects of Internet Usages on Female Students Academic and Personal Behaviors 9 students' (weak students') usage patterns and compare their usage behaviors and patterns with good or excellent students' usage patterns and extracting all similarities and dissimilarities.

5.1 Analyzing Usage pattern's From Different Aspects

1) Relationship between Internet Usages and Undertaken Program

One of the basic questions related to Internet usages are concerned on finding relationship between Internet usage behavior and users undertaken programs during examination week. In Figure 7, the horizontal axis shows hours per a day (24 hours) and vertical axis shows the percentage of users which belongs to different programs. In this part, just 3 programs, BTech, Mtech and MCA are presented.

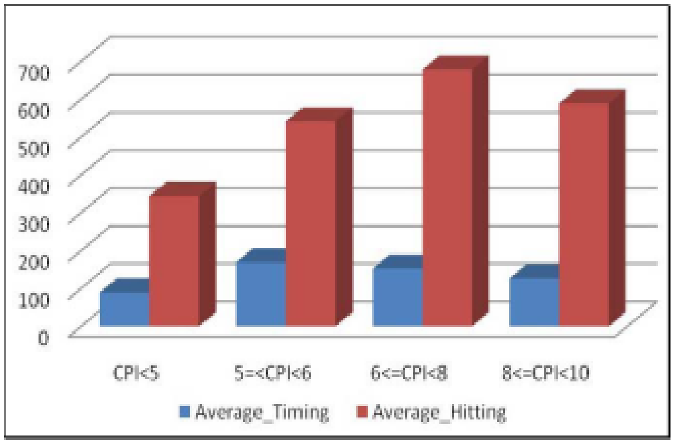

Figure 6. Female Students Average Time Spent on Internet and Hits # vs. CPI

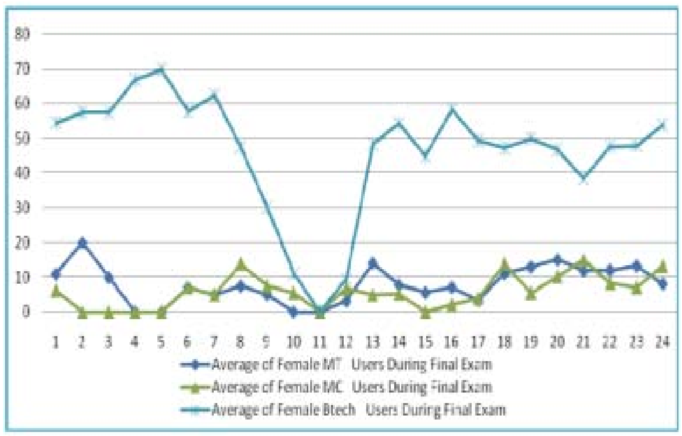

Figure 7. Internet Usage vs. Users Undertaken Programs

From Figure 7, we can observe that at 11AM all branches are having similar behaviors and that is minimum users had connection to Internet.

- Majority of users during final examination week belongs to BTech program

- Minority of users belongs to MCA program

- In some hours, there are similar behaviors within the same undertaken program. For example, at 4, 5, 6, 7 AM there is a matching on MCA and Mtech users' behaviors and percentage of usages.

2) Relationship between Semester and Internet Usage Patterns

The other analysis understands the relationship between different semesters and students Internet usage behaviors. Figure 8 presents semester wise comparisons between users' Internet usages during final examination weeks.

3) Number of Visited Pages (Hit#) in different Periods of a Semester

Figure 9 differentiates average number of hits (number of visited pages) per a day by users in different periods of a semester including during semester, final examination days and during sectionals examination (mid-term examination) weeks. The horizontal axis represents 24 hours a day and vertical axis represents the average number of visited pages (hits#) by users. From this figure, it is clear that, majority of visited Web pages belong to final examination weeks and minority of visited Web pages belong to during the semester. Other results from this figure shows that there is no increase in time spent on Internet during examination weeks. The reason for majority number of visited Web pages during examination weeks might be increase in speed of search during examinations by female users or increasing number of requests for different Web pages during these periods.

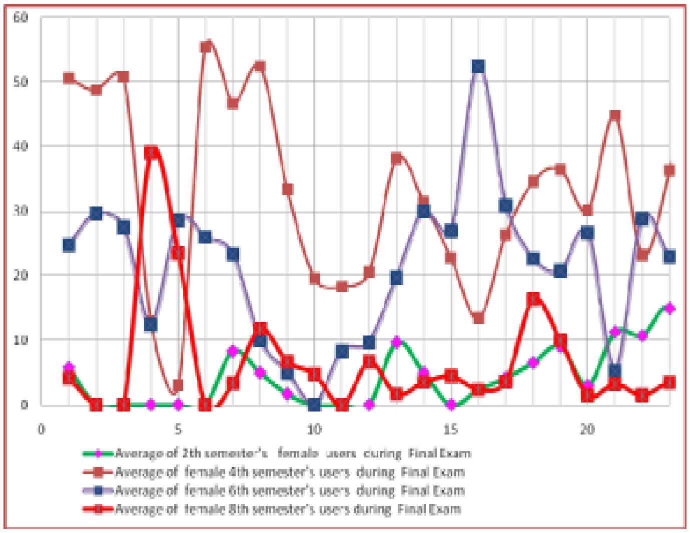

Figure 8. Relationship between different semesters and students Internet usage behaviors

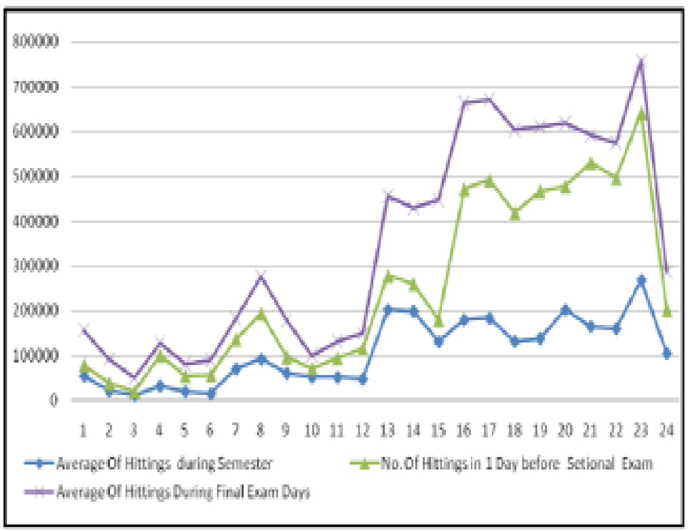

Figure 9. Average of Hit# in different Periods

4) Different factors effecting on Female Users Usage Behaviors

4.1 AC & NAC Usages during a Semester

Average number of visited unique Websites in different hours of a day, based on content and structure of Websites (based on Website categorization mentioned in [4]) is presented in Figure 10. In this figure, the horizontal axis shows 24 hours a day and vertical axis shows the number of visited unique websites.

This figure shows the number of unique visited websites in AC and NAC category. From this figure, during a semester:

- Maximum number of visited websites by female students belongs to NAC

- Minimum number of visited websites belongs to 0-5 and 11AM and 5PM each day

- Maximum number of visited Websites belongs to 9AM and 11PM

4.2 Various Internet Usage Behaviors in Different Periods

Our analysis shows that there are brief differences on usage patterns on AC and NAC Websites during different periods of a semester and are shows in Figure 11.

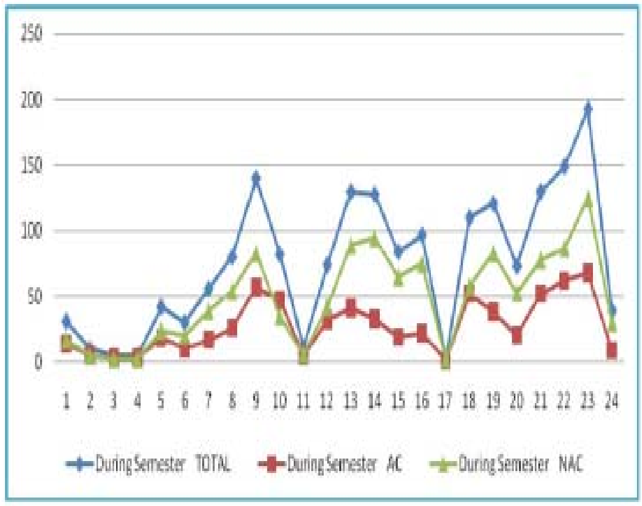

Figure 10. Number of Visited Unique Websites per a day during a Semester

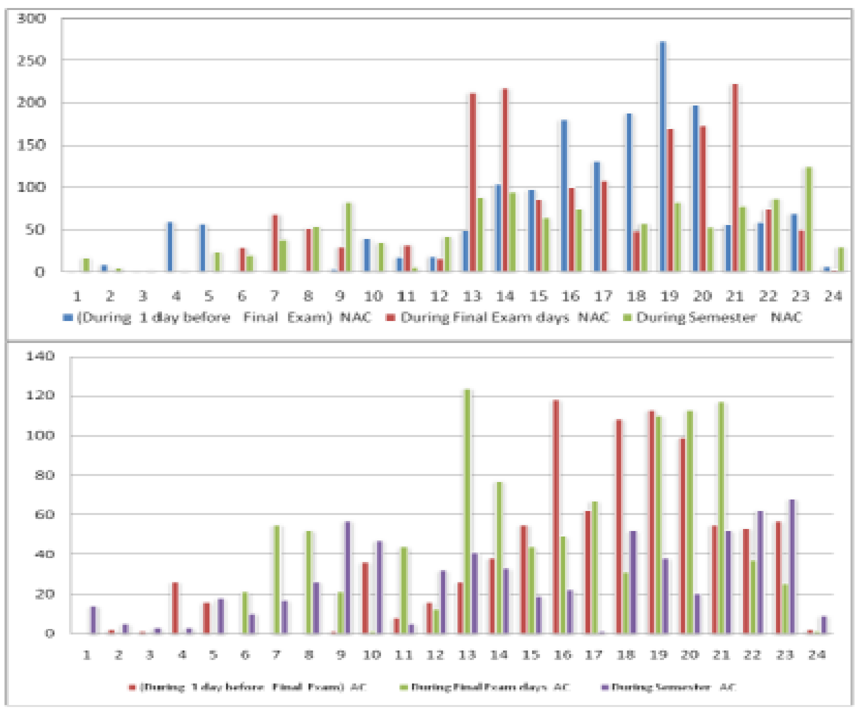

Figure 11. AC and NAC Usage in Different Periods

Horizontal axis in both cases shown in Figure 11, represents 24 hours a day and vertical axis represents the number of visited unique websites for AC and NAC category.

Some of the important observations from this figure are:

- Usage of NAC Websites during a day before examination and during examination weeks was increased.
- Maximum number of visited NAC Websites was 280 at 7PM and during a day before final examination weeks.
- Usage of AC Websites during final examination weeks and a day before examination week was increased.
- Maximum number of visited AC Websites was 122 at PM and during final examination weeks.

The noticeable results concerned on increasing the number of NAC Websites which are visited by users during examination weeks. Our hypothesis assumes that female users, due to tensions, most of them less visit NAC Websites, but as per log files analysis results shows, totally reverse of our hypothesis. The reason may be related to their limitations for going out of hostel after 8PM, lack of social connection with classmates and of tension for various reasons [4].

Based on Figure 6, most of users belong to academically good students; this seems a strong Internet resources' access has positive effects on female users' activities and cope of different stresses during examination periods.

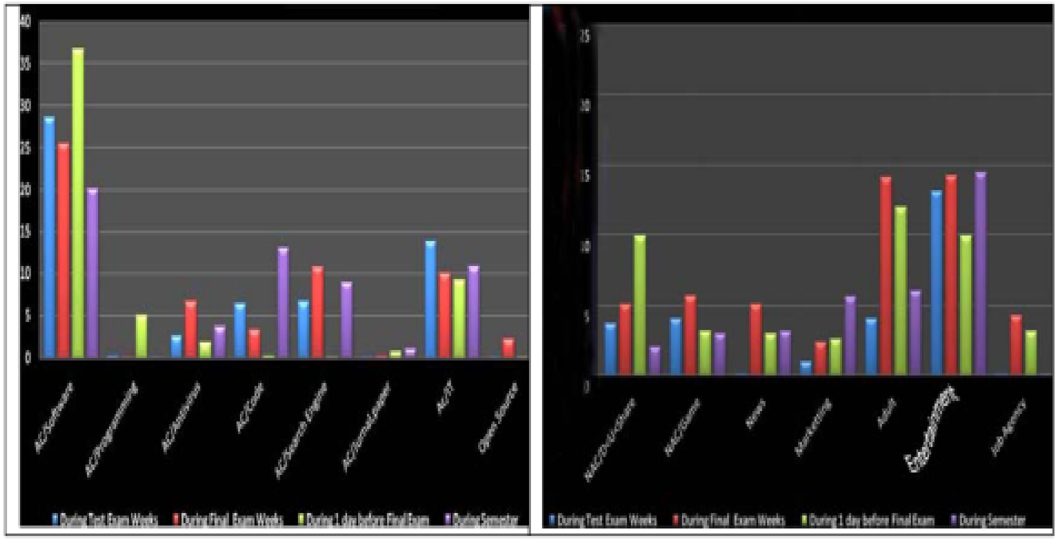

Figure 12. AC and NAC Sub-Categories Usages in Different Period

4.3 Comparing Female Students popular Unique (AC & NAC) Visited Sub-Category Websites

Whenever we discuss about AC and NAC categories, the obvious question raised would be what is the majority of usage category and belong to which sub-categories?

Figure 12 presents both AC and NAC sub-categories usage percentages in different periods of a semester.

In Figure 12, the horizontal axis shows different sub-categories of AC and NAC Websites, the vertical axis shows the percentage of usages in different periods of a semester. These periods include during final examination weeks, a day before examination, during semester and during test-examination week.

From Figure 12, the following observations can be made:

- The most interesting and visited AC Websites belongs to Software downloading including anti-virues and other tools

- Maximum usages of search engines and open sources belongs to examination weeks

- Majority of NAC Websites sub-categories belongs to EN, Adult, and SN.

- Adult Websites' maximum usage during a semester belongs to examination weeks and a day before examination

- SN Websites' maximum usage belongs to a day before examination weeks and examination week

- EN Websites maximum usage belongs to mid-term and final semester examiantion weeks and minimum usage belongs to a day before examination weeks

Regarding this results our hypothesis is approved, which is, during examiantion weeks, Internet resources are most useful for students sice their usage results declares that maximum usages of search engines belongs to examination weeks.

4.4 EN Vs. SN Usages Time on Different Periods of a Semester

A comparison between SN and EN usages in different periods of a semester is presented in Figure 13.

From Figure 13, the horizontal axis shows 24 hours a day and vertical axis shows the time spent by users in minutes in these categories (SN and EN) in different periods of a semister and include during a semester, during final examination weeks and a day before examintion.

Some of interesting results from Figure 13 are:

- Maximum time spent are on SN Websites during different periods of a semester

- Maximum time spent on SN was during a semester and minimum belongs to a day before examination weeks

- Female users' spent time on EN Website less than SN Websites

- Minimum time spent on EN Websites belongs to a day before examination weeks

- Maximum time spent on EN Websites belongs to during semester

- Some intereting points regarding equal usage time in different periods are dedicated. For example, at 3, 4AM, time spent on SN is equal to time spent on EN Websites during a semester which is 200 minutes.

- During a day before examination, minimum usage of EN Websites is dedicated, time spent in this category of Websites at 1, 6, 7, 8, 9AM is empty.

- Similar usage time is extracted for before examiantion weeks and examination week at 0 to 5 and 10AM in EN Websites usage.

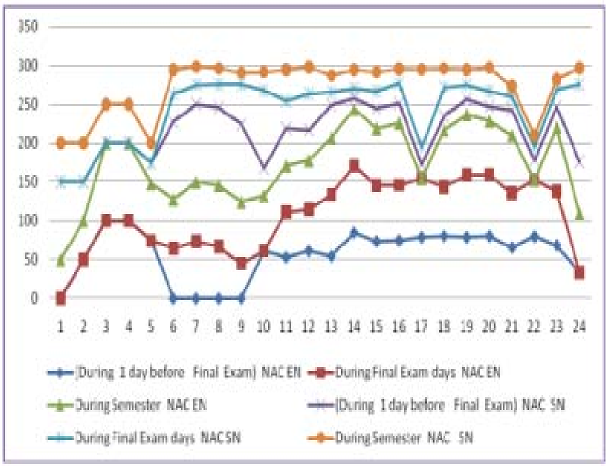

Figure 13. A comparison between SN and EN usages in different periods of a semester

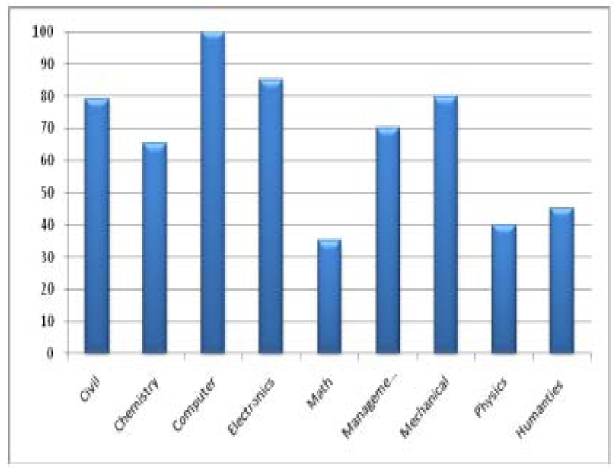

Figure 14. Faculty members/Professors % of Usage from Different Departments

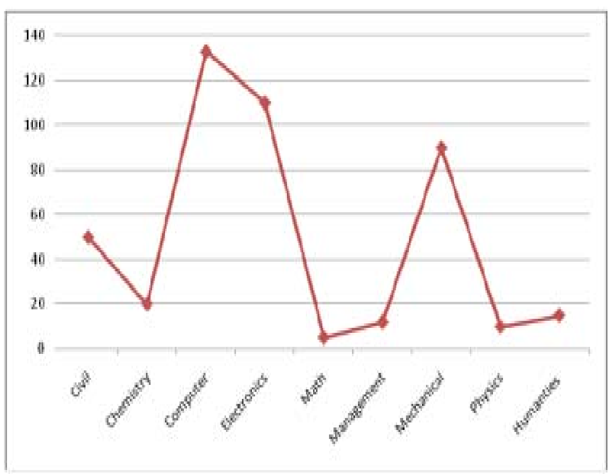

Figure 15. Faculty Members/Professors Time spend on Internet per a Day (in minutes)

6. Female Faculty Members/Professors Internet Usage Behaviors Relationship with Their Professional Life

Figure 14 shows the percentage of faculty members/professors from various departments which had continual usage of Internet resources. In this figure, the horizontal axis shows the names of different departments and the vertical axis shows the percentage of continual users from each department.

From Figure 14, majority of Internet usage belongs to computer science department and minority belongs to mathematics and physics departments'.Maximum time spent on Internet by female faculty members/professors belongs to Computer science department and minimum time spent belongs to mathematics department.

7. Conclusion

In this investigation, we have analyzed female users' Internet usage behaviors from various aspects. Based on our results, different behaviors and Internet usage patterns in different category of Websites of female students are observed based on their undertaken branch, and semester and time spent in different hours of a day. Similarly, differences in Internet usage behaviors are detected in female faculty members'/professors' usage patterns and behaviors from different departments.

From our observation, we found approximately 65% of students' Internet usage belongs to NAC and 35% belongs to AC category of Websites and during examination weeks NAC Websites usage is more than AC Websites. During examination weeks, majority of Internet usage belong to SN and undesirable Websites including adult Websites, etc. Since, average CPI of users is in the range (6<=CPI<8), and they were academically good students, therefore, to cope with stress and tension during examination periods female students are accessing NAC Websites.

8. Acknowledgment

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References

[1] Dutch, Jonathan. The Internet and Its Effect on Generations of Women in America, http://www.scribd.com/doc/17271135/The-Internet-and-Its-Effect-on-Generations-of-Women-in-America

[2] ODP Classification Scheme http://www.dmoz.org/

[3] Wikipedia Classification Scheme http://en.wikipedia.org/wiki/Classification_scheme

[4] Oskouei , Rozita Jamili., Chaudhary, B.D. (2010). Internet Usage Pattern by Female Students (A Case Study)IEEE, 7th International Conference on Information Technology: New Generation , ITNG 2010 ,Las Vagas, USA, p.1247-1250.

[5]Srivastava, J., R.Cooley, R., Deshpande, M.,Tan, P.N(2000).Web Usage Mining: Discovery and Applications of Usage Patterns from Web Data, ACM , SIGKDD Jan.

[6] Srivastava, Jaideep. Web mining: Accomplishments and Future Directions, University of Minnesota , USA, http://www.ieee.org.ar/downloads/Srivastava-tut-paper.pdf

[7] Tanimoto, Steven L. Improving the Prospects for Educational Data mining, http:// www.educationaldatamining.org/UM2007/Tanimoto.pdf

[8] Boyd, D.M.,Ellison,N.B (2007). Social Sites: Denition, History and Scholarships, *Journal of Computer Mediated Communication*, article 11, http://jcmc.indiana.edu/vol13/issue1/boyd.ellison.html

[9].Koohang, A. (2004). Students Perceptions toward the use of the digital library in weekly web-based distance learning assignment portion of a hybrid program, *British Journal of Educational Technology*, 35 p.617- 626.

[10] Cooley, R., Mobasher, B., Srivastava, J. Web mining , Information and Pattern Discovery on the World Wide Web , *In:* proceedings of the 9th IEEE International Conference on Tools with Articial Intelligence (ICTAI97)

[11] Kosala, R., Blockeel, H., (2000).Web mining Research: A Survey, SIGKDD Explorations

[12] Buchnner, A.G, Mulvenna , M.D. , Anand , S.S, Hughes, J.G, (1999). An internet-enabled knowledge discovery process, *In:* Proceedings of 9th International Data base Conference. Hong Kong, p.13-27.

[13] Pierrakos, Dimitrios., Paliouras, G., Papatheodorou, C., Spyropoulos, C.D. KOINOTITES: A Web Usage Mining Tool for Personalizations, http://www.ionio.gr/ papatheodor/papers/F63.pdf Exploring Different Affects of Internet Usages on Female Students Academic and Personal Behaviors 17

[14] Srivastava, J., Cooley, R., Deshapa, M.,Tan, P-N (2000). Web Usage Mining: Discovery and Application of Usage Patterns from Web Data. ACM SIGKDD (2) 12-23.

[15] .Chen, M.S., Han, J., Yu, P.S (1996). Data mining: An overview from a Database perspective" IEEE Tranaction on knowledge and data Engineering, 8 (6) 866-883.

[16] Fayyad, U., Piatetsky-Shapiro, G.and Smyth, P. (1994). From Data mining to Knowledge Doscovery: An Overview, *In:* Proc. ACM KDD.

[17] Xu, Jianyun., Sung, A.H., Liu,Q. Behavior Mining of Fraud Detection http://jrpit.acs.org.au/jrpit/JRPITVolumes/JRPIT39/JRPIT39.1.3.pdf

[18] .Hao, M.C Ladisch, J..Dayal, UHsu, M..Krug,A (2001). Visual Mining of E-Customer Behavior Using Pixel Bar Charts" http: /www.hpl.hp.com/techreports/2001/HPL-2001-144.pdf

[19] Manavoglu, E., Pavlov, D., Giles, C. Lee (2003). Probabilitistic, "User Behavior Models ", 3rd IEEE International Conference on Data Mining (ICDM03).
[20] Yada, K., Motoda, H., Washio, T.Miyawaki, A(2004). Consumer Behavior Analysis by Graph Mining Technique, Springer Verlag Berlin Heidelberg. p.800-806.
[21] Adar, E., weld, D.S.Bershad,B.N., Gribble,S.D (2007). Why We Search : Visualizing and Predicting User Behavior" , www.2007/Track: Data mining
[22] Zhau, B..Hui, S.C.Fong, A.C.M (2005). Discovering and Visualizing Temporal-based Web Access Behavior" , Proceedings of the 2005 IEEE/WIC/ACM International Conference on Web Intelligence (WI05)
[23] Hu, J., Zeng, H.J., Li, H., Niu,C. Chen, Z (2007). Demographic Prediction Based on Users Browsing Behaviors Behavior www 2007/ Track: Data Mining , session: Predictive Modeling of Web Users
[24] Wikipedia http://en.wikipedia.org/wiki/Social network
[25] http://www.whatissocialnetworking.com/
[26] Srivastava,Jaideep (2008). IEEE ISI 2008 Invited Talk (III) ,Data Mining for Social Network Analysis
[27]Figl, K., Kabicher, S., Toifl, K. (2008). Promoting Social Networks among Computer Science Students , 38th ASEE/IEEE Conf. Frontiers in Education , Saratoga Springs, NY.
[29] Zhou, B., Hui, S.C., Fong, A.C.M (2005). Discovering and visualizing Temporal-based web access Behavior" ,Proc. 5th Conf. on Web intelligence.
[30]Sanders,Jo (2005).Gender and Technology in Education: A Research Review, June 2005 , wwwjosanders.comlpdfi'gendertech0705.pdf
[31] Kim, Sunha., Chang, Mido (2007). The Differential Effects of Computer Use on Academic Performance of Students from immigrant and Gender Groups: Implications on Multimedia Enabled Education, Ninth IEEE International Symposium on Multimedia 2007-Workshop.
[32] Liccardi, Haria., Ounnas, Asma., Pau, Reena, Massey, Elizabeth., Kinnunen, Pavi., Lewthwaite, Sarah., Midy,Marie-Anne, Sarkar, Chandan.The Role of Social Networks in Students' Learning Experiences http://portal.acm.org/citation.cfm?id=1345375.1345442
[33] Adar, Eytan., Weld, Daniel S., Breshad, Brain N., Gribble,Steven D. Why We Search:Visualizing and Predicting User Behavior , http://www2007.org/papers/paper520.pdf
[34] El-Halees, Alaa. Mining Students Data to Analyzing Learning Behavior: a Case Study" , http://eref.uqu.edu.sa/files/eref2/folder6/f158.pdf
[35]Suneetha, K., Krishnamoorthy, K.R (2009). Identifying User Behavior By Analyzing Web Server Access File, IJCSNA *International Journal of Computer Science and Network Security*, 9 (4).
[36]Jamali, Mohsen., Abolhassani, Hassan (2006). Different Aspects of Social Network Analysis, IEEE/WIC/ACM International Conference on Web Intelligence.
[37]Llaria, Liccardi., Asma Onnas, Reena Pau. The Role of Social Networks in Students' Learning Experiences, http://portal.acm.org/citation.cfm?id=1345375.1345442
[38] Oskouei, Rozita Jamili, (2010). Analyzing Different Aspects of Social Network Usage, IEEE, International Conference on Technology for Education(T4E'10) IIT Bombay, Mumbai , July 1-3.
[39] Minaei, Behruz., Kashy, Deborah A., Kortemeyer, Deborah A., Punch, Wiliam F. (2003). Predicting Students Performance:An Application of Data Mining Methods With An Educational Web-Based System, *In*: 33rd ASEE/IEEE Frontiers in Education Conference.
[40] Oskouei, Rozita Jamili, (2010). Impact of Non-Academic Websites Usage on Female Students Academic Performance (A Case Study), IEEE , International Conference on Educational and Network Technology(ICENT 2010), China, June 25-27, 2010
[41] Oskouei, Rozita Jamili, Chaudhary, B.D (2010). Relationships Between Academic Performance and Usage Pattern of Non-Academic Websites by Gender Group , IEEE, International Conference on Educational and Network Technology(ICENT 2010), China, June 25-27, 2010
[42] Oskouei, Rozita Jamili (2010). Identifying Students Behaviors Related to Internet Usage Patterns, *In*: IEEE, International Conference on Technology for Education(T4E'10) IIT Bombay, Mumbai , July 1-3.
[43] Oskouei, Rozita Jamili (2010). Modeling Female Students Entertainment Websites Usage Patterns, International Conference on Informatics Cybernetics and Computer Applications(ICICCA2010), Bangalore, India, 19-21 July.

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