PASSIVE MONITORING IN THE WORKPLACE: DESIGN GUIDELINES FOR SELF QUANTIFIED EMPLOYEE FEEDBACK SYSTEM

Tufail, Muhammad; Lee, Haebin; Kim, Myungjin; Kim, KwanMyung
UNIST Ulsan National Institute of Science and Technology, Republic of Korea (South Korea)

Abstract

The use of online social networking services is considerably more accessible today due to advances in ICT in workplaces. Employees are spending more time on Internet engaging in non-work-related activities, such as maintaining personal networks, interacting with friends, streaming music and video, checking sports scores and following Web bookmarks by visiting various online social venues. As such, organizations are increasingly concerned about maintaining a stable workforce, and thus they make the use of monitoring systems. However, the current monitoring practices violate employees' reasonable expectation of privacy, decrease self-determination and cause employees to complain and possibly increase intent to quit jobs. We present the use of passive monitoring in the workplace as a new tool to observe employees' Internet activities with objective measures. Based on Self Quantified movement, we aim to design a system that can passively monitor employees, provide visualization feedback based on their Internet usage activities, and allow employees to understand the implications of their actions concerning the boundary between work-related and non-work related Internet activities.

Keywords: Research methodologies and methods, Service design, Technology, Online social networking services, Employee feedback

Contact:
KwanMyung Kim
UNIST Ulsan National Institute of Science and Technology
Graduate School of Creative Design Engineering
Republic of Korea (South Korea)
kmyung@unist.ac.kr

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1 INTRODUCTION

Online social networking services (OSNs) are considerably more accessible today due to advances in ICT and the prevalence of smartphones in workplaces (Wu et al., 2013). Studies have shown that employees are spending more time on OSNs engaging in non-work-related activities, such as maintaining personal networks, interacting with family and friends, streaming and downloading music and video, checking sports scores and following Web bookmarks by visiting various online social venues (Pitt and Bennett, 2008). The increasing use of OSNs represents a concern for organizations about maintaining a stable workforce, and it seems that many organizations cannot prevent the use of OSNs during working hours as they haven't yet implemented proper policies on Internet use. Many organizations are aiming to enhance their employees' productivity in order to achieve strong revenues and avoid the wasting of resources. Added to this, wasting time over non-work-related activities represents a massive unseen cost to organizations. For example, if there is an organization with a single department with only a few employees and each of them spends an hour a day on non-work-related activities, it equates to a whole employee wasted (Babinchak, 2011). Organizations are, therefore, understandably interested in monitoring their employees' Internet usage within the context of ethical considerations. The use of employee monitoring systems has become frequent for organizations. Monitoring systems record employees' Internet activities and keystroke data and take screenshots of the websites visited; they subsequently warn employees about their usage (Spitzmuller and Stanton, 2006). In fact, organizations have the right to ensure that job performance is enhanced and that workplace time is not wasted or abused and to know how their equipment is being used and in what capacity. However, it may be detrimental to the behaviour of dedicated and trustworthy employees to be monitored based on subjective judgements. Because, when employees begin to feel they are being monitored and that their organization doesn't trust them, their mental well-being is adversely affected, which may potentially increase their stress levels and decrease the efficiency of their job performance (Ciocchetti, 2011). In fact, technology used for monitoring purposes is not biased; however, it is important to understand how monitoring methods are designed and applied, how their use influences employees' reactions, and how efficient they are in the workplace (Alder, 2001).
The purpose of this study is to design a system that can passively monitor employees and provide persuasive visualization feedback based on their Internet usage activities. To this end, the proposed system has two sides: quantified self (QS) and passive monitoring. The QS approach has been used in a variety of tools to collect information exclusively intended for self-reflection and self-monitoring, with the aim of giving employees information about their personal behaviours, choices and lifestyles. This approach originated from the self-quantified movement – a new lifelogging research branch that aims to incorporate technology to acquire and collect information on different aspects of people's daily lives (Marcengo and Rapp, 2014). On the other hand, passive monitoring can capture user activities passively and can be triggered without the user being directly contacted, involved or requested to take action (Rivera-Pelayo et al., 2012). As a way to join these two aspects, this study presents the design of an employee feedback system as a new QS tool that can be used to help employers improve their employees' productivity.

2 LITERATURE REVIEW

There is much debate about the impact of the extensive usage of OSNs on employee productivity. Some organizations are very positive about the use of OSNs; others are very concerned about the reduction in productivity, while the majority, possibly, lie somewhere in the middle. Employee productivity is the time spent by an employee to execute duties within a proper timescale in the workplace in order to produce the desired outcomes (Ferreira and Du Plessis, 2009). However, OSN is a form of social interaction based on the typical characteristics of human behaviour, which fulfils the need to connect with people to share a common interest and to gain knowledge through contact. The use of OSNs is prevalent among employees, with a huge number of online users gaining access to services such as Facebook, Twitter, YouTube, LinkedIn, MySpace, Tumblr and Instagram, and new networks emerging. Some studies indicate that OSNs are mainly used for social purposes, typically related to maintaining and establishing offline relationships. This means that employees may feel obliged to maintain their social networks, which may lead to excessive use of OSNs (Kuss and Griffiths, 2011). Therefore, the mass appeal of OSNs can potentially be a cause for concern, particularly in terms of the increasing amounts of time employees spend engaged in a variety of online activities. This behaviour may also be potentially addictive and may affect employee productivity (Lober and Flowers, 2011).

In recent years, the addiction literature has widely reflected on the presence of behavioural addictions, such as Internet addiction, which refers to compulsive or problematic Internet use; researchers have developed subjective constructs such as scales for measuring social media disorder (SMD) and Internet gaming disorder (IGD) as well as clinical interviews to diagnose OSN addiction on an individual basis (Van den Eijnden et al., 2016). However, the use of employee monitoring and surveillance technology has become prevalent, with most organizations monitoring employees' online Internet usage, including creating logs of all Internet sites visited. Studies have found that some employees feel annoyed and distrustful in response to monitoring, and some avoid the use of monitoring systems by modifying the configurations (Spitzmüller and Stanton, 2006). It appears that the success of employee monitoring systems depends on employees' willingness to comply with their use. Ciocchetti (2011) added that monitoring practices are all unpleasant if abused, and, thus the new monitoring regime in the organization should require employers to provide advance notification of monitoring practices to employees.

Quantified self (QS) is a new branch of research that uses monitoring and rendering of human-behaviour-generated data to persuade people to change their practices in everyday-life (Marcengo and Rapp, 2014). The purpose of collecting human-generated data is to allow for self-monitoring and self-reflection related to some kind of change or improvement in people's behavioural, psychological and medical conditions. The QS movement was founded in 2007 by Gary Wolf and Kevin Kelly, the editors of Wired. The QS movement is based on the concept of the self and uses the question "who am I?" to provoke answers based on our everyday actions, thereby responding to the need to quantify behaviours. In the QS format, data collection is performed, and the information is then displayed and connected to determine possible correlational patterns. The data is collected through specific sensors and devices dedicated to particular applications, e.g., SenseWear, Fitbit and Zeo. The present study identifies the approach to addressing issues related to the problematic use of the Internet to design a new QS tool that passively monitors employees and provides them with persuasive visualization feedback based on their OSN usage activities. The most important issue in the QS movement is data collection. The proposed approach makes the use of passive network traffic measurements to collect OSN traffic datasets. Recent research efforts have been absorbed in the application of machine learning (ML) to identify network traffic classification assembled using flow statistical features. ML techniques can search for and identify pragmatic patterns of interest in a traffic dataset for classification purposes. Furthermore, the flow-statistical-feature-based traffic classification can be determined using supervised classification algorithms or unsupervised classification algorithms (Murat and Schmidt, 2010).

3 RESEARCH APPROACH

3.1 Study design and Participants

In this section, the user observational method is presented by which desktop computer users were observed through two different monitoring tools. The objective of this section is twofold: (a) to infer whether the data obtained from the two monitoring tools have similar patterns over time, and (b) to explore user activities over time. The data was collected over time and stored in a computer for further analysis. The data collected was time series data, which was in the form of an ordered sequence of values of a particular variable (user activity as the dependent variable) at equally spaced time periods (the timestamp as the independent variable). A user activity is the action of a user when using Internet resources. A timestamp is the time slot during which the activity was performed. The objective of the analysis is to identify patterns in the sequence of user activities over time, which are correlated but balanced in time.

Twenty-five full-time research students were recruited at the office of a well-known research institute in South Korea. They had desktop computers connected to the Internet. Prior to the experiment, a short survey was conducted with them regarding the use of the activity logger program on their computers, which monitored their activities and generated reports. Only 20 participants agreed to a compromise in which the reports would be treated with complete confidentiality and would be entirely anonymous.

The monitoring session was conducted in a working day from 9:00 AM to 7:00 PM, using both the activity logger program and the network monitoring tool. Activity loggers basically record overall user activities such as file events, keystrokes, programs, mouse events and website logs with timestamps. We

considered only website logs with timestamps to determine their relevance in relation to the data obtained from the network monitoring tool.
For network monitoring, a single PC with the Linux operating system and Wireshark software was used. Wireshark is a network packet analyser used to capture real-time network traffic with detailed information. The network connection to the PC was configured in a promiscuous mode, which refers to the special mode of a network interface card for receiving all traffic on the network even if it is not addressed to it. Normally a network interface card ignores all traffic that is not addressed to it. However, the promiscuous mode does not work in a protected network because packets from or to other computers cannot be decrypted by the network interface card. To avoid this limitation, we granted access to the office's local network switch and configured its mirror port for monitoring all the traffic, because a switch using port mirroring sends a copy of all network packets to a monitoring PC[1].

3.2 Data analysis

Internet traffic data captured using network monitoring tools generally contain a huge amount of network packets, some of which are irrelevant and represent background noise. In the present study, the Internet traffic data were filtered to obtain user-activity-dependent traffic, and ignore all other periodic traffic that contained user-activity-independent traffic data, such as periodic acknowledgment of the false-positive rate of P2P applications in participants' computers. User-dependent activity protocols, which indicate that the traffic was user activity dependent and contained true-positive cases, are presented in Table 1.

Table 1. User dependent activity protocols

Protocol	Type	Description
HTTP	IP, TCP	HTTP traffic
SSL, TLSv1.2	IP, TCP	Associated with TLS and HTTP

The list of protocols, as shown in Table 2, was excluded from the analysis because these protocols contain a false-positive rate of user-activity-independent traffic.

Table 2. User independent activity based protocols

Protocol	Type	Description
ARP, VRRP, AARP	Network	Periodic request to convert an IP address to DLC address
DB-LSP-DISC	IP, UDP	Periodic request to acknowledge Dropbox LAN sync discovery
NBNS, LLMNR, DNS, QUIC, BROWSER, SNMP, DHCP	IP, UDP	Same as DNS, translate human-readable names to IP addresses (Netbios-ns)
SSDP	UDP (TCP*)	Discover plug & play devices with uPnP and uses unicast and multicast address
IPX SAP		Internetworking based on service advertisement
ICMP, IGMP	IP	Periodic request for internet control messages
HP		HP switch protocol
CDP and STP		CISCO discovery and spanning tree
BJNP		Canon scanner command discovery
ALLJOYN-NS		All joyn message service

After collecting the data of all the participants and excluding the periodic and false-positive cases from the Internet traffic data, the following procedure was used for further analysis.

3.2.1 Participants and Dataset classification

We made profiles of website logs obtained from the activity logger program and the Internet traffic data for each participant. Website logs were collected from each individual computer, while Internet traffic

[1] Wireshark and Promiscuous mode, https://www.wireshark.org

data were featured according to the IP address of each individual computer in the subnet. Each profile consisted of two datasets: website logs and Internet traffic data.
From the website logs, we extracted the websites-visited count for each profile and saved it as a CSV file for further analysis. Subsequently, we filtered all Internet traffic data for Web packets by HTTP/HTTPs requests and all DNS responses, and stored them as a CSV file. Subsequently, we classified the websites-visited count as a general-website count, and an OSN-website count. Similarly, we classified Web packets into two classes: general Web packets and OSN Web packets.

3.2.2 Sample aggregate average

In time series analysis, the score observed over time can be aggregated to identify the patterns of interest over time. Thus, we took the aggregate averages of the numbers of the general-website count and the OSN-website count. The same procedure was conducted for the numbers of general Web packets and the numbers of OSN Web packets. In addition, using weighted moving average analysis (Holt, 2004) we computed the weighted averages of the past two observations (9:00 - 10:00, 10:00 - 11:00) of the OSN in both samples and used their values as a prediction of the present mean of the distribution.

3.2.3 Data representation

The sample aggregate averages were capitalized and categorized in order to show the patterns of interest. The data was split into 10 equal time intervals of an hour. By taking the aggregate average number of website logs and Internet traffic data of all the participants, we noticed that these major time intervals during a working day had significant unique data flow patterns. Table 3 shows the average numbers for the general-website count and the OSN-website count in the left columns and the average numbers for the general Web packets and OSN Web packets in the right columns with their respective time intervals.

Table 3. Aggregate average data statistics

Time periods	Website logs		Internet traffic data	
	GWS count	OSN count	GWS packet	OSN packet
9:00 -10:00	4.3	5.6	11.6	7.6
10:00 -11:00	4.6	2.1	15.1	8.3
11:00 -12:00	9	5.3	14.6	7.6
12:00 -13:00	7.6	0.3	10.6	6.6
13:00 -14:00	8.1	6.8	16.3	12.3
14:00 -15:00	7	2.3	14.6	15.6
15:00 -16:00	9.1	7.6	11.3	10.2
16:00 -17:00	9.6	4.3	18.3	11.4
17:00 -18:00	15.8	4.8	25.8	8.8
18:00 -19:00	2.6	6.3	13.6	14.3

GWS = average numbers of general website; OSN = average numbers of online social networking

3.3 Data analysis results

As shown in Figure 1, the average values for the general-website count and for the OSN-website count are analogous, and both occur at relatively the same time periods. We also computed new values for the average obtained by computing a weighted average of the OSN counts, the value of the average from the last period and the current value of the OSN counts using weighted moving average time series analysis. As shown in Figure 1, the trending line shows variations in the OSN count over the following hours.

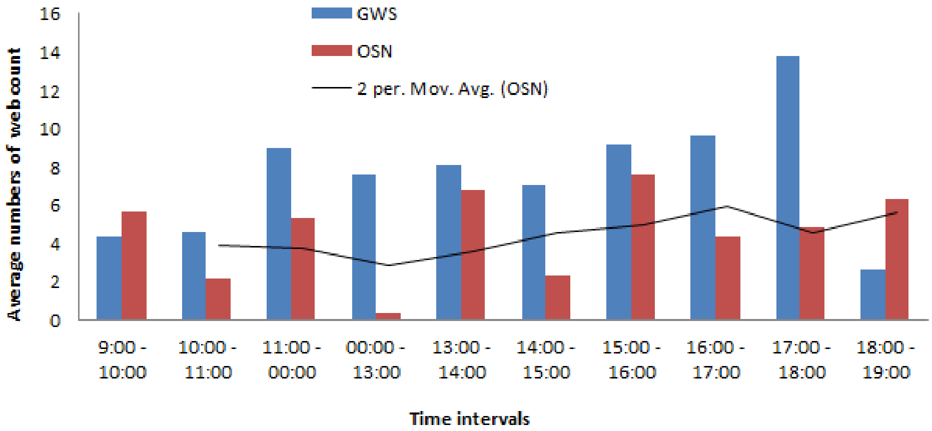

Figure 1. The average numbers of website log with time intervals

As shown in Figure 2, the average values of the general Web packets and the OSN Web packets are shown in Figure 2. The analysis of the Internet traffic data indicates that the average values of the general Web packets and the OSN Web packets are analogous, and both are acknowledged over the same time periods. We also computed new values for the average obtained by computing a weighted average of the OSN Web packets, the value of the average from the last period and the current value of the OSN Web packets. As shown in Figure 2, the trending line shows variations in the OSN Web packets over the following hours.

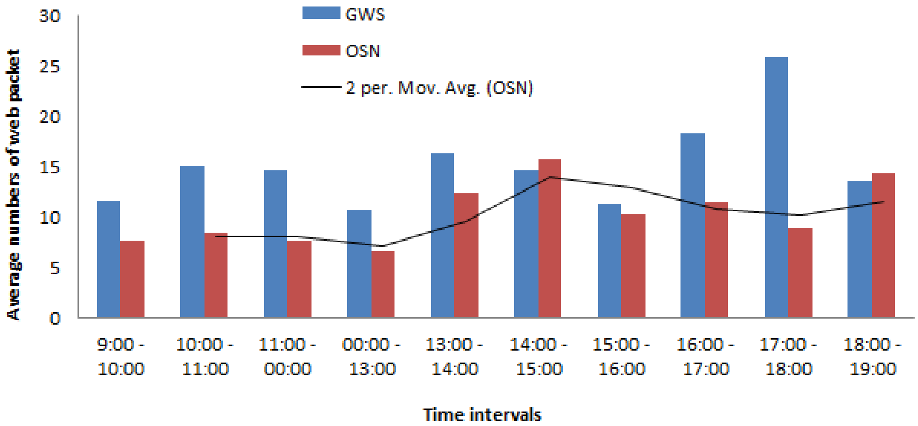

Figure 2. The average numbers of internet Traffic data with time intervals

It is confirmed from both analyses that the use of online social networking websites coincided with the use of general websites. It is clear that participants were using online social networking websites in conjunction with general websites, which may also include their work-related activities. In the above Figures, the general-website count/packet and the OSN-website count/packet have visibly similar patterns and both the website logs and the Internet traffic data are closely associated.

4 PROPOSED EMPLOYEE FEEDBACK SYSTEM

We acknowledged the same data patterns using both monitoring tools. We realized that the network monitoring tool, which we called passive monitoring, was computationally easier, more convenient, and less time consuming, and thus is appropriate for the design of an employee feedback system. The reason is that it makes the monitoring practice easy for the whole subnet and generates live traffic that can easily be analysed for user feedbacks. The proposed feedback system can capture real-time Internet traffic using Wireshark. Using feature selection, the system can automatically classify live Internet packets into two classes: general Web packets and OSN Web packets. Feature selection has been used in various studies on Internet classification (e.g., Nguyen and Armitage, 2008; Huang et al., 2009) because the selected subsets of the features, which are optimized for higher learning accuracy and have lower computational complexity, can improve the performance of machine learning algorithms by removing irrelevant and redundant features without losing classification accuracy. Based on the selected

features and classification, the proposed system can then quantify both classes with features using statistical analysis and can generate logs. If the logs contain a significant amount of OSN Web packets, the system can then generate a time-series visualization of activities for every individual employee. Time-series visualization techniques are used in pervasive systems as a form of passive triggering to change people's behaviour through self-motivation, which enables them to understand hourly variations in their activities over time without active participation (Forlizzi et al., 2007). There is also a growing trend in the consumer market to produce pervasive systems that support self-monitoring and that render human behaviour through visualization methods with a focus on persuading people to change their everyday practices, especially in areas of health, mood, fitness, energy conservation, emotions and communication (Lehto and Oinas-Kukkonen, 2011).
As shown in Figure 3, the proposed system contains three levels: physical/hardware level design, software environment level design and user activity visualization level design.

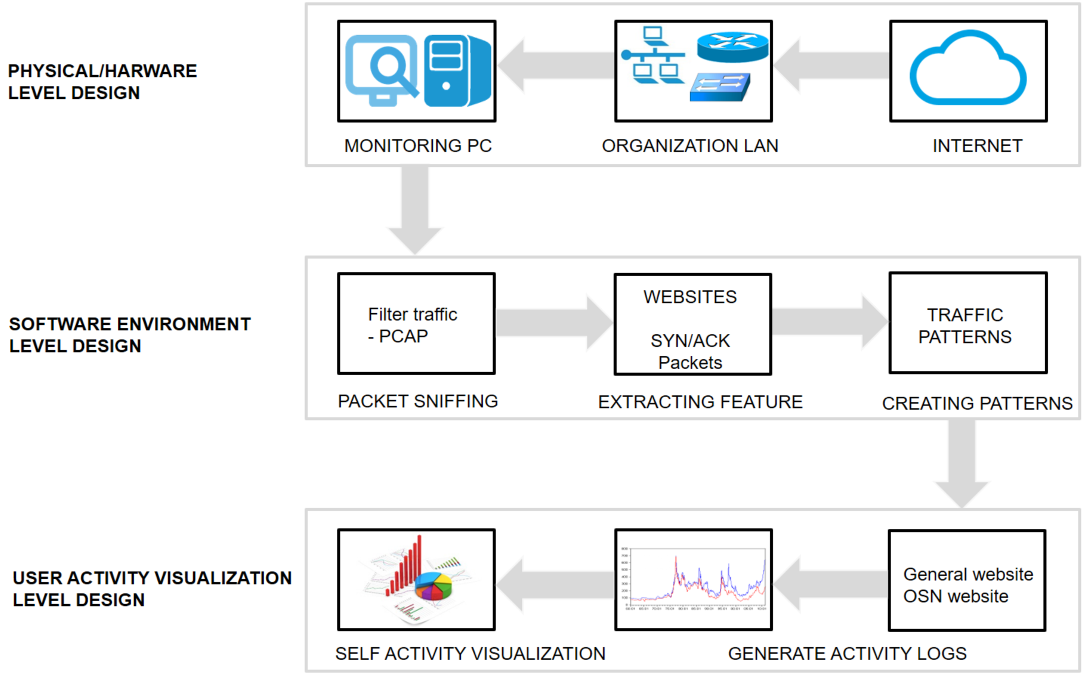

Figure 3. The Design of Employee Feedback System

4.1 Physical and hardware level design

This level demonstrates the physical structure of the environment, which includes a subnet of the organization with a network router or switch, Internet connection and a monitoring PC. The monitoring PC should be connected to the network switch using port mirroring. Port mirroring allows a network switch to send a copy of all network packets to the monitoring PC, whereas, normally, network traffic is hidden without configuring the mirror port (Zhang and Moore, 2007). The Linux operating system should be installed on the monitoring PC in order to configure the network identification card's promiscuous mode in case the port mirroring option is not available. This step is important and cannot be skipped because the Internet traffic of the whole subnet should be addressed to the monitoring PC to enable traffic classification in the later steps.

4.2 Software environment level design

At this level, a monitoring PC with the Linux operating system and Wireshark software should be configured to enable sniffing of the whole subnet's live Internet traffic. Tshark is the command-line interface of Wireshark, and is more promising because it works in the background and consumes less memory of a computer. During the sniffing, a package in Python (Pyshark) should be imported to allow parsing from a live capture, to filter user-activity-dependent protocols and to exclude user-activity-independent protocols (Tsoukalos, 2015). Subsequently, the Scikit-learn library for training and testing feature-selection ML classification in Python should be used to classify the Internet traffic into two classes: general Web packets and OSN Web packets (Nelli, 2015). These classes should be used with a suite of different statistical tests to select a subset of features that is small in size yet holds important and useful information about both classes. Feature selection is the process of supervised ML classification that identifies the smallest necessary set of features to achieve the accuracy goals and excludes irrelevant and redundant features in the traffic, which often have negative impacts on the accuracy and performance of most ML algorithms (Nguyen and Armitage, 2008). In feature selection, the filter method should be used to make independent calculations based on the general characteristics of the Internet traffic, which depends on a certain metric to rate and select the best subset before ML starts. A correlation-based feature selection (CFS) filter method with best-first is suggested for Internet traffic classification (Kim et al., 2008). For example, Pearson chi-squared test is used for true-positive cases from the classified Internet traffic.

4.3 User activity visualization level design

There are various potential applications for activity visualization, which often employ information presentations to increase users' awareness and change their behaviour. Activity visualization information differs from traditional feedback methods, as they present information in real-time situations, are context dependent, are aesthetically pleasing and are capable of enabling personal interpretation; they also don't disturb users unnecessarily, and they avoid the tendency to annoy them (Lau and Moere, 2007). To generate visualization logs of user activities in the proposed system, Pandas Python library should be imported for time-series analysis. At this point, the Pandas package can consolidate features using the Scikits.timeseries package to create a time series activity visualization log in which users can see variations in their activities with a particular time frame (Bernard, 2016). Employees in the workplace can understand and act on their habits as they receive updates about their activities. It is also important to note that the visualization of the activity logs should be displayed in charts such as bar, line, area and pie charts, because charts are a common way to display time-series data (Heer et al., 2009). The main purpose of the charts is to display information to employees for self-motivation through work-related and non-work-related activity comparisons with absolute value in real-time and over time (e.g., over a day, a week, or a month). We consulted Abela's (2008) chart selector system for the time-series data representation. A column chart and a line chart for the feedback system can enable the displaying of comparison data covering employees' work-related and non-work-related Internet activities over time. Employees can then compare their work-related activities and their non-work-related activities, which will motivate them to reduce their non-work-related Internet activities if their work-related activities are lower.

5 CONCLUSIONS

This study presents the promising use of passive monitoring in the workplace that observes employees' Internet activities using objective measures. This study furthers the design of an employee feedback system as a new QS tool in the field of quantified self movement. The purpose is to introduce a new paradigm shift in the employee monitoring field, because the current excessive and unreasonable monitoring systems often have a negative impact on employee productivity. Moreover, subjective monitoring practices in organizations invade employees' reasonable expectation of privacy, decrease self-determination, cause employees to complain and possibly increase employees' intent to quit, leading them to act stealthily in their respective compartments when conducting personal activities. This can also cause employees to fear even doing work-related activities.

This study acknowledged that passive monitoring of real-time Internet traffic is worthy to generate persuasive feedback for employees because it doesn't need to be installed or configured on each employee's computer, and most importantly it isn't based on subjective monitoring. This represents an improvement because most monitoring systems have to be installed and configured on each computer, and employees may be able to control or modify the configurations. The proposed system allows employees to see instant feedbacks on their Internet usage, keeping them focused on work-related activities and discouraging criminal or immoral usage behaviour. The advantages of online social networks shouldn't, however, be ignored, including business significance and information sharing for both employees and organizations, which, in the end, may enhance performance and productivity.

Therefore, parental control and strict rules over the use of online social networks in organizations can be problematic. Nevertheless, this use still needs to be reduced.
This study found a significant amount of use of OSNs along with general website usage by the participants. The amount of use of general websites may include work-related activities; however, the consistent usage of OSNs may have a negative impact on the performance of employees' work-related activities. The amount of time employees spend on the use of OSNs per day should be a matter of concern for any organization. It cannot be ignored that organizations, being the owners of the equipment used, have the right to ask for an adequate level of performance and good results and can expect the best return on their investment. There may be some employees using social media for knowledge and experience sharing with their counterparts, but this cannot be generalized and can still be achieved in proper and effective ways if the management of employees' social network activities exist.
A real-time Internet traffic classification using ML techniques has enabled a variety of applications in a variety of areas, such as quality of service, security and intrusion detection in the network. The method of classifying Internet traffic in the proposed system has implications for educational institutes, which can allow them to identify traffic related to various OSN services. They can put some constraints on the use of such services for students to increase their study and research performance.
This study contributes to the QS movement field by providing a new QS tool and provides a direction to researchers seeking to quantify the massive use of OSN as an abnormal human function by developing novel techniques and digital devices under the umbrella of QS movement. Future work will be conducted to design different presentation methods, such as direct feedback via SMS/message, social peer pressure, explicit incentives and ambient visualization displays to observe the influence of the methods on employees. However, more research is needed to truly understand the effect of monitoring on employees, including how they approach their work-related tasks and their attitudes towards the organization.

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